Where Does Advertising Content Lead You? We Created a Bookstore to Find Out*

Ilya Morozov
Northwestern University

Anna Tuchman
Northwestern University

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Abstract

We study how advertising content influences consumers' decisions. To this end, we create a simulated online bookstore that imitates a real online shopping experience. We then conduct a pre-registered and incentive-compatible experiment in which we randomly expose store visitors to display ads, randomizing both advertising exposures and content. We find that ad content plays a major role in shaping advertising effects. Ads that reveal a book's low price consistently increase demand for the advertised book relative to ads that do not reveal price. By contrast, ads that reveal the book's genre induce some consumers to search and buy the book but lead others to reject it without search. We show these polarized responses can increase or decrease the total number of searches and purchases of the advertised book depending on the share of consumers who favor the revealed genre. Our findings suggest that advertisers should carefully choose which product attributes to reveal in their ad copies. We also show that revealing product attributes in ads does not change the total amount of search. Taken together, our results suggest the primary role of ad content is to affect consumers' beliefs about the advertised book rather than to alter the perceived benefits from search.

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1 Introduction

An advertisement is like the opening act of a play: presenting the right information can engage the audience from the first curtain rise, while failing to do so may squander their attention. Accordingly, the success of a campaign may depend on which product attributes firms choose to spotlight in their ads. By advertising specific attributes, firms hope to entice consumers into considering their product more closely. Chevrolet and Ford, for instance, highlight horsepower, fuel efficiency, and durability in their truck ads, while Apple and Samsung emphasize the battery life, camera quality, and price of their smartphones. Although there is broad consensus that choosing the right ad content can indeed play a crucial role in driving ad effects[1], firms receive contradictory advice on which product attributes to advertise: some practitioners advocate emphasizing unique product attributes, while others advise revealing attributes that matter most to consumers.[2]

In this paper, we study how consumers respond to ad content that reveals product attributes, and we provide both theoretical and empirical results to guide firms in making their ad content choices. Studying these questions presents several challenges. Most researchers do not observe ad creatives and can only present indirect evidence of ad content effects.[3] Even when they do observe ad content, it is hard to disentangle how different elements of multi-dimensional ad creatives shape advertising effects. Further, researchers need to address endogeneity concerns that arise because firms target ads at specific consumer segments and during particular time periods. For example, firms may advertise prices during the season of holiday discounts, in which case the ad content consumers see will correlate with temporary demand changes.

[1]Nielsen Catalina reports that almost 50% of the sales lift from advertising can be attributed to ad creatives (Nielsen, 2022). Similarly, a 2022 study from Meta shows that following their recommended practices for making ad creatives can increase short-term sales 1.2 to 7.4 times and long-term sales 1.2 to 2.7 times (Meta, 2017).

[2]For example, the creative management platform Confect explains that product attributes highlight "what makes your product different, unique from the rest" and are "typically the deciding factors" driving consumer choices. They claim that, based on their analysis, ads showing attributes perform 44% better than ads that do not describe the product (https://confect.io/blog/custom-labels-dynamic-product-ads). Meanwhile, the The Ecomm Manager newsletter recommends that marketers "list the product attributes that will matter most to your prospective buyer."

[3]A few studies that do not observe ad content present indirect evidence suggesting that consumers learn product attributes from ads. For example, Anand and Shachar (2011) document that consumers make choices that seem more aligned with their tastes after being exposed to ads, and Ackerberg (2001) shows that advertising primarily affects consumers who have little experience with the advertised brand.

To address these challenges, we design and implement an experiment that randomizes both advertising exposures and content. Using web development tools, we create a simulated online bookstore that imitates a real online shopping experience. We then conduct a pre-registered experiment in which we recruit around 11,500 participants on Amazon Mechanical Turk and ask each of them to select an e-book from our store. When participants visit the store, we expose them to display ads, randomizing whether an ad is shown and also whether the ad copy reveals the book's genre ("genre ad"), its price ("price ad"), or does not reveal any attributes other than the title and cover image ("plain ad"). The participants then browse the store and purchase e-books as they normally would when shopping online. We record the entire search process using advanced tracking tools. To elicit realistic shopping behavior, we make the experiment incentive-compatible by sending participants the e-books they selected.

Using experimental data, we study the effects of advertising content on consumers' decisions. Laying the foundation for our main analysis, we first estimate *exposure effects* by comparing the behavior of consumers under plain ads to that in the no ad control group. Exposure effects may arise because ads signal the book's high quality (Nelson, 1974; Milgrom and Roberts, 1986) or because they help consumers discover the advertised book and offer an easy way to click through to the book's product page (Arbatskaya, 2007; Armstrong et al., 2009; Haan and Moraga-González, 2011). Consistent with these theories, we find that plain ads substantially increase the search and purchase rates of the advertised book. These exposure effects establish a benchmark against which we measure the incremental effects of revealing attributes in ads.

Turning to our main analysis, we estimate *content effects* by studying how consumers respond to attribute ads relative to plain ads. Using a simple search model, we formulate hypotheses on how attribute ads should affect consumers' search and purchase decisions. In our experiment, attribute ads reveal either a book's low price – a vertical attribute that appeals to all consumers ("price ad") – or genre – a horizontal attribute that indicates the book's match value ("genre ad"). The model predicts that revealing a low price should weakly induce all consumers to search and purchase the advertised book. By contrast, revealing genre should induce some consumers to search the book because they learn it matches their tastes while discouraging others from searching it because they learn it is a bad match.[4]

We find our experimental results to be remarkably consistent with these theoretical predictions. Relative to plain ads, price ads increase searches and purchases of the advertised book regardless of consumers' genre preferences. Revealing price makes the ad, on average, 26% more effective at driving searches and 35% more effective at driving purchases. By contrast, genre ads induce polarized responses relative to plain ads: consumers who favor the revealed genre become more likely to search the book, while those who do not favor the genre discard the book without searching. As a result, revealing genre makes the ad more or less effective depending on the share of consumers who favor the revealed genre. For example, revealing a mainstream mystery genre makes the ad 15% more effective at driving searches and 12% more effective at driving purchases, whereas revealing a niche romance genre makes the ad less effective, decreasing ad effects on searches by 31% and on purchases by 16%.

At a high level, our results suggest revealing attributes in ads can influence choices by changing consumers' beliefs about the advertised book's attributes. At the same time, we find that ad content does not significantly alter how consumers conduct their search or how satisfied they are with their final choices. For example, price ads do not make consumers more likely to sort books by price or search other inexpensive books, and genre ads do not lead consumers to use genre-related filters or to search other non-advertised books of the same genre. Revealing attributes in ads also does not change the total number of books consumers search or the time they spend searching. Thus, in our setting, ad content primarily affects consumers' beliefs about the advertised book's attributes instead of changing attribute salience or altering the perceived benefits from searching.

Our findings have several implications for managers who design ad campaigns. We document that revealing an attribute in ads can generate a spectrum of effects, from strongly positive to strongly negative, depending on how consumers value the revealed attribute. Consequently,

[4] Johnson and Myatt (2006) show that this polarized response may rotate the demand curve clockwise. Anderson and Renault (2006) find a similar effect in their model. The attention model of Gossner et al. (2021) also predicts polarized responses and demand rotations. In their model, advertising can generate negative effects when it helps consumers eliminate an unappealing option that does not match their tastes.

advertisers should understand the distribution of tastes across consumers before choosing which attributes to reveal in their ads. Advertisers may also benefit from jointly optimizing the content of their ads and the scope of their advertising campaigns. If the product's attributes are relatively niche, the advertiser may want to run a targeted campaign, selectively revealing these attributes to consumers who value them the most. Our results suggest there can be meaningful gains from such targeting: we show that targeting genre and price ads based on estimated conditional ad effects increases the search probability by 14% relative to the best non-targeted policy. By contrast, an advertiser restricted to mass advertising campaigns may want to reveal appealing vertical attributes such as a low price.

Our paper contributes to the literature on whether and how consumers respond to ad content.[5] Most papers provide only correlational evidence of ad content effects (Stewart and Furse, 1986; MacInnis et al., 2002; Chandy et al., 2001; Liaukonyte et al., 2015; Hartnett et al., 2016; Anderson et al., 2016; Du et al., 2019; Bruce et al., 2020; Dall'Olio and Vakratsas, 2023; Guitart and Stremersch, 2021). For example, Liaukonyte et al. (2015) find that TV ad effects correlate with whether the ads have an action, information, emotion, or imagery focus, and Du et al. (2019) find stronger ad effects for creatives that consumers find informative and likable. Although these correlations are suggestive, they might be misleading if firms target ad creatives at specific customer segments or show them during peak-demand periods. A few authors attempt to address content endogeneity using quasi-experimental methods, but they characterize their own results as correlational and call for more experimental work on ad content (Lee et al., 2018; Tsai and Honka, 2021; Dall'Olio and Vakratsas, 2023).

Only a few papers address the endogeneity of ad content using randomized experiments. Lodish et al. (1995) conduct a meta-analysis of 96 TV advertising copy tests and find stronger ad effects for ad copies that introduce attributes such as flavor, brand, form, and packaging. Bertrand et al. (2010) randomize dimensions of ad content and find that ads for bank loans are more effective when ad content induces an intuitive rather than reasoned response. Finally, Biswas (2020) runs an

[5]Early papers in this literature document the prevalence of informative ad content (Resnik and Stern, 1977; Stern and Resnik, 1991; Abernethy and Franke, 1996), but they do not study the effects of ad content on consumers' choices.

experiment on a food delivery app and shows that revealing discount information in ads increases demand for advertised restaurants.[6] Building on these papers, we develop a theoretical framework to assist firms in choosing which attributes to advertise, and we present experimental evidence that consumers' responses to ad content are consistent with the theoretical predictions. We also use detailed browsing data to study whether ad content influences how consumers conduct their search, which is not done in this prior work.

Several papers study how advertising affects search by applying observational methods to non-experimental data (Honka et al., 2017; Tsai and Honka, 2021; Ursu et al., 2021a; Chiou and Tucker, 2022). A notable exception is Fong (2017) who analyzes a field experiment designed to study how targeted marketing emails affect consumer search on a retailer's website.[7] Building on these papers, we design and implement an experiment in which we can cleanly identify the causal effects of ads on search by randomizing both ad exposure and content.

Finally, our paper complements the prior work on measuring consumer search in controlled lab experiments (Gabaix et al., 2006; Reutskaja et al., 2011; Shi et al., 2013; Ursu et al., 2021b). Inspired by this work, we create our own bookstore where we experimentally manipulate ads and collect more detailed search data than are usually available to advertising researchers. Our bookstore can be accessed from any device with an internet connection, which enables us to recruit thousands of participants. Further, the realism of our store increases the external validity of the experimental results.[8] We showcase this approach and illustrate how one can design an incentive-compatible experiment in which products are electronically delivered to participants. By doing so, we hope to provide a blueprint for other researchers interested in adopting a similar methodology

[6] A few papers study ad content effects in randomized experiments but do not manipulate attributes revealed in ads. Sudhir et al. (2016) randomize advertising content in a field experiment on charity ads but focus on measuring consumers' behavioral responses to ad content that is unrelated to attributes. Xu et al. (2014) randomize the source of a price ad in a lab experiment and find that participants respond more positively to price ads run by dealers than those run by manufacturers.

[7] Fong (2017) estimates the causal effect of ad exposures, whereas we focus on advertising content. Kalyanam and Kim (2024) implement a field experiment on a B2B company's website to study how revealing information about assortment breadth and quality affects search by influencing consumers' beliefs about search benefits.

[8] In a parallel effort, Dang et al. (2022) also create a simulated shopping platform to gather search data, but they focus on understanding the reasons behind search revisits rather than measuring ad effects.

in their work.[9]

2 Advertising Content Effects and Consumer Search

2.1 Theoretical Framework

A consumer with unit demand chooses among J books available in the bookstore. The utility consumer i derives from purchasing book j equals $u_{ij} = -\alpha_i p_j + \gamma_i g_j + \varepsilon_{ij}$, where p_j is book j's price; $g_j \in \{0,1\}$ is its genre; and α_i and γ_i are the consumer's price sensitivity and genre taste.[10] We assume the heterogeneous price sensitivities α_i are positive and distributed with the CDF $F_\alpha(\cdot)$ and the heterogeneous genre tastes γ_i are distributed with the CDF $F_\gamma(\cdot)$. Thus, price p_j is a vertical attribute in the sense that, other things equal, all consumers prefer to pay less. By contrast, genre g_j is a horizontal attribute that may be liked by some consumers and disliked by others. Finally, ε_{ij} captures other horizontal attributes that determine book j's match value such as its detailed plot description. There is no outside option, so each consumer must choose a book.

Following Greminger (2022), we assume consumers learn about books via the following process of search and discovery, which closely approximates how consumers search in our bookstore. Upon visiting the store, the consumer observes n_d books on the front page, which form the initial awareness set, S_0. The consumer learns the prices p_j of these books but not their genres g_j or attributes ε_{ij}. We make this assumption because in our bookstore consumers see prices on product list pages, but they need to click on books to learn their genres and other attributes.

After seeing the initial set of books S_0, the consumer sequentially decides whether to discover additional books, search a previously discovered book, or purchase a previously searched book. The consumer can discover additional books by navigating to the next product list page, which adds n_d books to the awareness set and reveals their prices. To discover books from page l, the

[9] We created a written tutorial that provides detailed instructions on how to create an online store and conduct experiments within the store. Researchers can access the tutorial at github.com/ilyamorozov/adContent.

[10] We use two genres for illustration. It would be straightforward to extend this model to an arbitrary number of genres.

consumer must pay the discovery cost $c_d^l > 0$. Alternatively, the consumer can search an already discovered book by navigating to its product detail page. To search a book, the consumer must pay the search cost $c_s > 0$. Searching a book reveals all its attributes, thus revealing the entire utility u_{ij}. The consumer keeps making sequential search and discovery decisions until they make a purchase or exhaust all search opportunities.

We assume the consumer expects that prices are drawn from a distribution with CDF $F_p(\cdot)$ with mean $\bar{p}$ and support $[0, p^{max}]$, that genre is $g_j = 1$ with probability q, and that attributes ε_{ij} are drawn from the distribution with CDF $F_\varepsilon(\varepsilon)$ on a support $[\underline{\varepsilon}, \bar{\varepsilon}]$. To simplify exposition, we assume prices p_j, genres g_j, and attributes ε_{ij} are independently distributed so that the consumer cannot use the attributes they already know to infer the ones they have not yet learned.[11]

2.2 Ad Content Effects

Our goal is to study the effects of ad content over and above any effect of being exposed to an ad. To this end, we first establish a benchmark for measuring ad content effects. Consider a "plain ad" for book $k \notin S_0$ of genre $g_j = 1$ whose organic listing resides on page $l(k) > 1$ and suppose this ad does not reveal any attributes other than the book's title and cover image. We assume a plain ad moves the book into the consumer's default awareness set S_0, reducing its discovery cost to zero. Because the ad does not reveal genre or price, the consumer needs to pay a search cost c_s to reveal these attributes.[12] Proposition 1 shows that the plain ad increases the search and purchase probabilities of the advertised book k, assuming this book's initial discovery cost is sufficiently high. We relegate all proofs of this section to Appendix A.

Proposition 1 (Exposure Effects). A plain ad increases the average search and purchase probabilities of the advertised book as long as its original discovery cost $c_d^{l(k)}$ is sufficiently high.

[11] In principle, consumers may believe that books' prices correlate with unobserved quality or match values. Because the range of prices in our store is fairly narrow, it is unlikely that such correlations play an important role.

[12] In our experiment, we only advertise books whose names and covers are relatively nondescript. Therefore, it makes sense to assume that consumers cannot infer other book attributes from the plain ads.

One can interpret Proposition 1 as saying that plain ads make consumers aware of the advertised book, as in Honka et al. (2017) and Ursu et al. (2021a), or that they reduce the effective cost of searching the advertised book.[13] Alternatively, plain ads may signal to consumers that the advertised book is of high quality.[14] Both mechanisms predict that a plain ad should increase searches and purchases of the advertised book. Because separating these explanations is not our main focus, we remain agnostic about the mechanisms behind exposure effects and instead turn to modeling the incremental effects of ad content.

Consider an ad that reveals a horizontal attribute, the book's genre. We assume a genre ad generates the same exposure effects as a plain ad, but it additionally reveals the book's genre to consumers. Revealing genre g_k sends consumers a noisy signal of utility u_{ik}, but they still need to pay the search cost c_s to learn the price p_k and attributes ε_{ik}. Proposition 2 shows that relative to plain ads, genre ads may increase or decrease demand depending on the share of consumers who value the revealed genre g_k.[15]

Proposition 2 (Content Effects: Revealing Genre). (a) Relative to a plain ad, a genre ad increases the search and purchase probabilities for consumers who like the revealed genre ($\gamma_i > 0$), decreases them for consumers who dislike the revealed genre ($\gamma_i < 0$), and does not change them for indifferent consumers ($\gamma_i = 0$).
(b) Relative to a plain ad, a genre ad increases the average search and purchase probabilities of the advertised book if there is a sufficient share of consumers who like this book's genre. On the other hand, a genre ad decreases the average search and purchase probabilities if there is a sufficient share of consumers who dislike the genre.

To gain intuition, suppose a publisher of the book *The Shadow of the Gods* by John Gwynne advertises the book as a fantasy story about mages and dragons. After seeing this ad, fantasy lovers

[13] Several theoretical consumer search papers view ads as reducing search costs (Arbatskaya, 2007; Janssen and Non, 2008; Armstrong et al., 2009; Haan and Moraga-González, 2011).
[14] For example, see Nelson (1974) and Milgrom and Roberts (1986).
[15] The theoretical literature on match value advertisements discusses similar results (Grossman and Shapiro, 1984; Meurer and Stahl II, 1994).

may become more interested in inspecting this book, as they have just learned that it matches their tastes well. By contrast, readers who dislike fantasy may conclude that this book is not for them. Learning its genre from the ad has convinced them that they should reject the book without searching. As Proposition 2a shows, advertising should then increase searches and purchases of this book among fantasy lovers and reduce them among consumers who prefer other genres, leading to polarized decisions. In turn, Proposition 2b implies that the net impact of these effects is ambiguous. In fact, the total demand for the advertised book may decrease if the negative response from consumers who dislike fantasy outweighs the positive response from fantasy aficionados.

Now consider an ad that reveals a vertical attribute – the book's price. As with genre ads, a price ad generates the same exposure effects as a plain ad but additionally reveals the book's price to consumers. Revealing price sends consumers a noisy signal of utility, but consumers still need to pay the search cost c_s to learn the remaining attributes g_k and ε_{ik}. Proposition 3 posits how consumers should react to price ads:

Proposition 3 (Content Effects: Revealing Price). The following two results hold if the advertised book is sufficiently inexpensive:
(a) Relative to a plain ad, a price ad increases the search and purchase probabilities of individual consumers regardless of their genre tastes γ_i.
(b) Relative to a plain ad, a price ad increases the average search and purchase probabilities of the advertised book.

When the ad reveals that book k is unusually cheap, as is the case in our experiment, all consumers view the revealed price as a positive signal of utility and thus become more likely to search the book. Although they still do not know this book's other attributes, the book now looks more appealing than it did before they saw the ad (Proposition 3a). This positive effect on search translates into additional purchases, thus increasing the average purchase probability of the advertised book relative to that under the plain ad (Proposition 3b).

3 Store Design and Advertisements

3.1 Bookstore Design

We create a realistic online bookstore using open-source website development software and populate it with a custom assortment of books. We use several plug-ins to serve display ads, and we collect detailed search data from all store visitors using advanced consumer-tracking software (see details in Appendix B.1). This software tracks everything consumers do in the store, including how many product list pages they visit, which books they click on, and whether they use filters, sorting tools, or search queries.

The store offers only one product category: electronic books. We chose this category because e-books can be electronically sent to participants, making it feasible to conduct a large-scale incentive-compatible study. The typical product list page displays books in two rows with five books in each row (see Figure 1). The store has 10 product list pages, and all consumers initially land on the first page. Consumers can navigate to other product list pages by clicking on buttons at the bottom of each product list page. Following the standard layout of online bookstores, such as Amazon or Barnes & Noble, we design product list pages so that they reveal basic information about books including the title, author, price, and cover image. Throughout our experiment, we keep books' prices and rankings the same for all consumers. Clicking on a book in the product list directs the consumer to the product page, which additionally reveals the genre of the book and a detailed description of its plot (see Appendix Figure A7).

The bookstore offers several search tools. Consumers can enter a search query or sort books by price (low to high or high to low). Each product page also shows non-personalized book recommendations, which feature three randomly selected books of the same genre (see Appendix Figure A8). From a product page, consumers can go back to the product list, navigate to the genre subcategory by clicking on genre tags, or click on a recommended product. To purchase a book, consumers can add it to the cart and complete the check-out process (see Appendix Figures A9-A10).

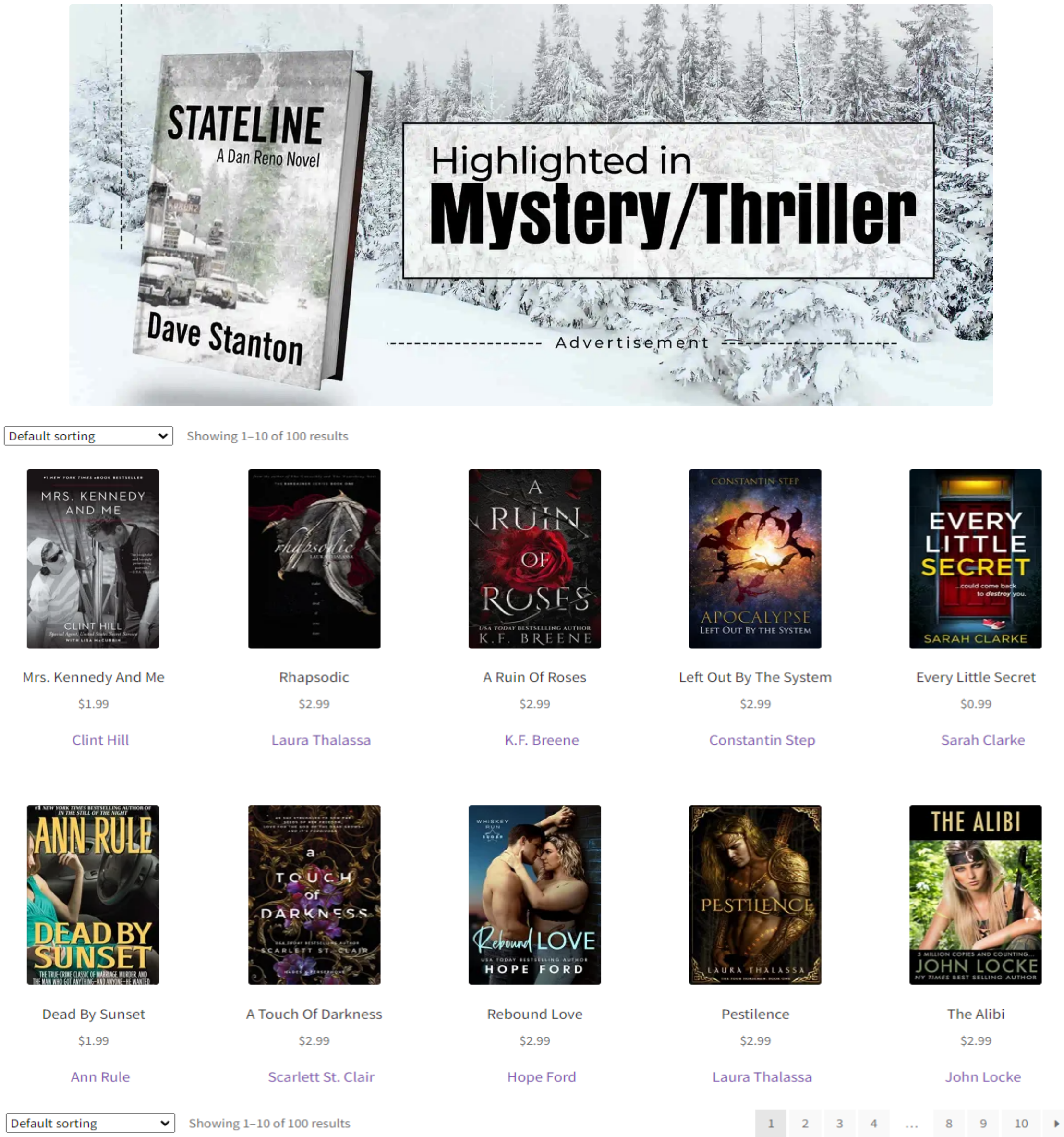


Figure 1: **A display advertisement on the first product list page.**

3.2 Book Selection

We populate our bookstore with an assortment of 100 books. To create a meaningful search task for consumers, we include books from five different genres: biography/memoir, fantasy, mystery/thriller, romance, and science fiction. We select inexpensive but high-quality books because we want to interest consumers in making a purchase, while also minimizing the expected cost of the experiment. To achieve this, we take books from Amazon bestseller lists and select 20 books of each genre that are priced under $3. We set the books' prices equal to the current Amazon prices, which range between $0.99 and $2.99, and we set the prices of the advertised books to $0.99 for reasons explained in Section 3.3. See Appendix B.2 for additional details on book selection.

3.3 Display Advertisements

The front page of the store displays a salient advertising banner (see Figure 1), similar to how major book retailers such as Barnes & Noble display ads on their websites (see Appendix Figure A11 for an example). Clicking on the banner in our store redirects consumers to the product page of the advertised book. The advertising banner is only shown on the front page of the store.

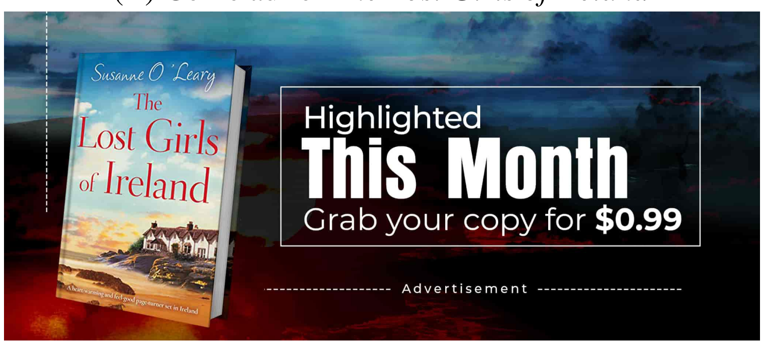
When choosing which books to advertise, we select books for which demand is likely to respond to advertising. Advertising an unappealing book would have little effect on choices, which would not give us sufficient power to precisely measure ad content effects. To avoid this issue, we select the mystery book *Stateline* by Dave Stanton and the romance novel *The Lost Girls of Ireland* (henceforth *Lost Girls)* by Susanne O'Leary. Both books are relatively popular within their genre subcategories on Amazon (e.g., customer ratings 4.2 and 4.3 out of 5 on Amazon). To enhance the appeal of these books, we reduce their prices from the original $2.99 on Amazon to $0.99, thus making them among the cheapest books in our store. We also choose these books because they have nondescript titles and covers that do not obviously reveal the book's genre, which helps us isolate the incremental effect of revealing genre in the ads. We place both books on the second page of the default product list to ensure we are not advertising options that are already salient. This placement also matches our theoretical setting in Section 2, where we assume that consumers

(A) Plain ad for *The Lost Girls of Ireland*

(D) Plain ad for *Stateline*

(B) Genre ad for *The Lost Girls of Ireland*

(E) Genre ad for *Stateline*



(C) Price ad for *The Lost Girls of Ireland*

(F) Price ad for *Stateline*

Figure 2: **Advertising copies used in the main experiment.** These ad copies were created by a professional graphic designer we hired on Fiverr.com, an online marketplace for freelance services.

do not observe the price or genre of the advertised book at the time of ad exposure.

In our main experiment, detailed in Section 4, we randomize participants into seven advertising conditions: a control condition and six treatment conditions corresponding to six different ad copies.[16] In the control condition, we hide the advertising banner from the front page and shift the organic book listings to the top.

Figure 2 shows the six professionally designed ad copies that we use for the main experiment. We first randomize participants into seeing advertisements for one of the two books, *Stateline* or *Lost Girls*. For each book, we further randomize participants into seeing one of the three advertising banners: (1) a banner with the generic text, "Highlighted This Month," that does not reveal any attributes other than the title and cover image ("plain ad"), (2) a banner that reveals the book's genre with the text "Highlighted in Mystery/Thriller" or "Highlighted in Romance" ("genre ad"), or (3) a banner that reveals the book's low price with the text, "Highlighted This Month: Grab Your Copy for $0.99" ("price ad"). Based on the power calculations conducted in a pre-test, we set the assignment probabilities to 4% for the control condition and 16% for each of the six treatment conditions. We describe how we implemented randomization in Appendix B.5.

4 Amazon Mechanical Turk Experiment

4.1 General Timeline and Sample Size Selection

We recruited participants from Amazon Mechanical Turk (MTurk). We first conducted two pre-tests based on which we selected a compensation scheme and conducted power calculations. Then, we pre-registered our main experiment and ran it between May 19, 2022, and August 3, 2022. Based on the pre-test data, we calculated that we would need at least 12,500 participants to measure the effects of advertising exposure and content. Because our budget was determined by an external grant, we committed to running the study until we exhausted this budget. In the end, we collected survey responses from $N = 16,088$ participants before we exhausted our budget, out of which

[16] A participant always sees the same ad regardless of the number of times they return to the front page.

$N = 11,498$ participants had complete browsing and purchase data. We provide further details on subject recruitment and attrition in Appendices B.3 and C.

4.2 Incentive Compatibility

We made the experiment incentive-compatible by fulfilling participants' orders. We gave each participant a budget of \$3, which is sufficient to purchase any book in the store. We told participants that we would conduct a lottery that gives each participant a 50% chance of having their order fulfilled. In addition to their baseline compensation of \$1.50, participants who won the lottery received their selected e-book and the remainder of their \$3 budget as a cash bonus. Participants who did not win received only the baseline compensation of \$1.50. Conducting a lottery helped us reduce the expected experiment cost while still incentivizing participants to select books they truly like.[17]

After the experiment, we conducted the lottery, manually bought books from Amazon, and sent personalized bonuses and book redemption links to the lottery winners. Participants could redeem and read their e-book using a free Amazon Kindle app on their e-book reader, browser, or phone. Because the purchased e-books could only be redeemed from the U.S., we only recruited participants who reside in the U.S.

4.3 Pre- and Post-Experiment Surveys

Participants were told that the study investigates their preferences for e-books. They first filled out a Qualtrics survey in which they reported their demographics and were asked to rank five book genres from their most preferred to their least preferred. We then informed participants about the incentive structure, explained that their choices would have real consequences, and asked them a comprehension question to ensure they understood their incentives.[18] Participants who passed the

[17] In our pre-test, participants in the 50% fulfillment condition behaved similarly to those in the 100% fulfillment condition. Participants searched less and were less responsive to ads in conditions with lower fulfillment probabilities (0% and 10%), indicating that in these conditions, they were not sufficiently incentivized to conduct search.

[18] About 75% of the participants who attempted the study passed the comprehension checks.

comprehension question were given a link to the bookstore and were asked to visit it, select their preferred e-book, and complete the check-out process.

After checking out, participants returned to the Qualtrics survey, and we asked them what they would prefer to do if they won our lottery: receive their selected book and the remainder of their $3 budget or forfeit the book and keep the entire $3 budget. The purpose of this question was to assess whether participants were genuinely interested in reading the books they selected.[19] To make the study fully incentive-compatible we implemented their decision on whether to keep the book or the money. We then also asked some general questions: what they thought the purpose of the study was, whether they remembered seeing advertising, how important genre and price were to their choice, and how much they would be willing to pay for *Lost Girls* and *Stateline*.[20]

5 Experiment Results

5.1 Experimental Data and Estimation

Our main sample includes participants who passed the comprehension checks, purchased a book in our store, and returned to the Qualtrics survey after completing the checkout process. Despite our instructions to use a standard browser, approximately 18% of the participants either used ad blockers or privacy-enhancing browsers that made it impossible for us to track their actions. We exclude these participants from the sample. Because participants are unlikely to change their browser privacy settings in response to seeing ads in our bookstore, we assume that this selection criterion is orthogonal to the experimental assignment. We further tested whether there was differential attrition across experimental conditions but found no evidence of such imbalances (joint $F = 1.64$ with $p = 0.132$). Our final sample includes $N = 11,498$ participants for whom we have complete browsing and purchase data. Appendices B and C provide further details on attrition, sample con-

[19]If we had given participants a "no choice" option during their shopping task, we would have lost data on the preferences of participants who chose the outside option. We borrowed our two-stage design from the literature on "dual response" conjoint surveys (Wlömert and Eggers, 2016).

[20]When asked about the purpose of the study, only 0.2% of participants mentioned anything about ads.

struction, and participants' demographics. Our data are available in a public GitHub repository, which researchers can use to replicate and extend our work.[21]

To understand whether we have generated realistic search and purchase behavior, we conduct several validation analyses (see Appendix D for details). First, we show that consumers engage in meaningful search: the average consumer spends 3.7 minutes in the store, opens 4.0 product list pages, and searches 1.9 unique books (see Figure A3). This search behavior is broadly consistent with the search behavior of actual consumers shopping for books online (see Figure A5), which we document using an external dataset from Comscore. Second, we show that consumers' book choices align with their self-reported genre preferences (see Figure A4). Third, we document that consumers do not exclusively purchase the cheapest books on the website to maximize their cash bonus (see Table A4). Finally, more than 60% of all participants decided they would keep their book if they won our lottery, and 27% of those who received a link redeemed their books, suggesting they truly liked the books they selected. Based on these results, we conclude that our experiment elicits meaningful search behavior and induces consumers to make choices that align with their book preferences.

Having validated our experimental data, we use them to estimate how consumers respond to ad exposure and ad content. In all analyses, we estimate ad effects using a linear regression model $y_i = \delta + \sum_{j=1}^{6} \beta_j \cdot T_i^j + \varepsilon_i$where y_i is the outcome variable, δ is the mean in the no advertising condition, β_j are ad effects, and T_i^j is an indicator that participant i is assigned to ad copy j. In Appendix C, we report randomization checks that use demographic variables and self-reported book preferences. While in some analyses the ATE estimates $\hat{\beta}_j$ are of direct interest, we study ad content effects by computing the differences (e.g., $\hat{\beta}_{genre} - \hat{\beta}_{plain}$), thus estimating the incremental effect of ad content relative to the effect of plain ads. We report robust standard errors in all analyses (Imbens, 2010).[22]

[21] The experimental data and replication codes can be accessed at github.com/ilyamorozov/adContent.

[22] Following best practices, in Appendix F, we also report the results while controlling for pre-treatment covariates (Duflo et al., 2007; Bruhn and McKenzie, 2009). Our results are robust to including these controls.

5.2 Exposure Effects

We start by estimating the effects of ads that do not explicitly reveal any attribute information. To this end, we estimate consumers' responses to plain ads relative to the control condition with no ads. The effects of plain ads establish a benchmark against which we measure the effects of ad content.

Appendix Table A5 reports the estimated advertising effects for *Lost Girls* in Panel A and *Stateline* in Panel B. Consistent with Proposition 1, we find that showing a plain ad significantly increases the search and purchase probabilities of the advertised books. Advertising *Lost Girls* makes the consumer $0.071/0.052 \approx 137\%$ ($p < 0.001$) more likely to search this book by visiting its product page and $0.037/0.028 \approx 132\%$ ($p < 0.001$) more likely to purchase it. We find even stronger advertising effects for *Stateline*. Showing a plain ad for this book makes consumers $0.072/0.050 \approx 144\%$ ($p < 0.001$) more likely to search it and $0.057/0.017 \approx 335\%$ ($p < 0.001$) more likely to purchase it. These exposure effects are primarily driven by clicks on the ad banner itself, rather than clicks on the organic product listing or product recommendations.[23]

Overall, these results illustrate that plain ads strongly increase demand for the advertised book. As discussed in Section 2, these exposure effects could arise because plain ads make consumers aware of a book, reduce its search costs, or signal its high quality. Testing these mechanisms is outside the scope of this paper. Instead, we now turn to discussing the incremental effects of ad content.

5.3 Content Effects

To visualize the effects of ad content, in Figure 3 we plot the average search and purchase probabilities of the advertised books across all conditions. In Table 1, we report the corresponding ATE estimates, their robust standard errors and p-values, and the p-values of pairwise t-tests.

We find substantial evidence of content effects. Revealing genre makes the ad for *Lost Girls*

[23] In Appendix Table A5, we also report the effects of plain ads on other outcome variables measured during different stages of the decision-making process (e.g, organic listing views, add-to-cart events, and book redemptions).

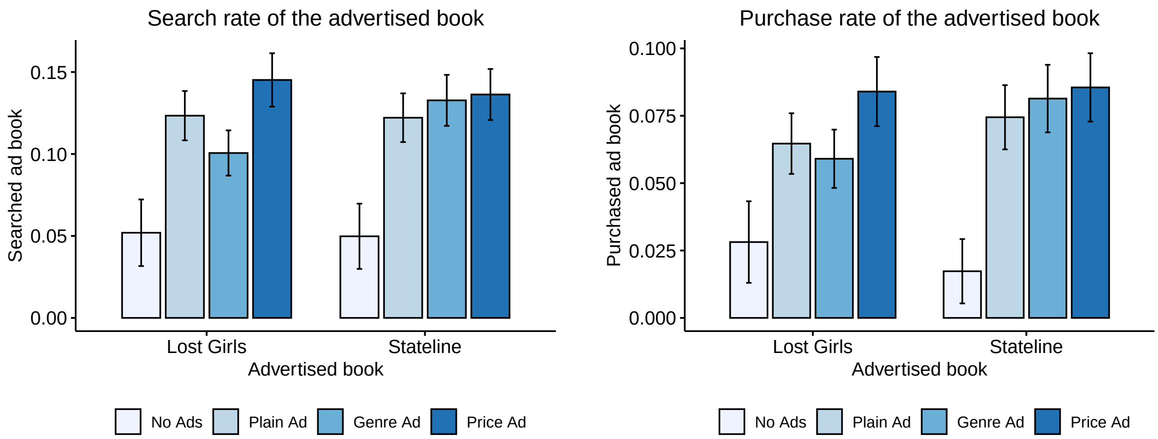


Figure 3: **Estimated advertising effects on searches and purchases.** The figure visualizes the average search probabilities (left graph) and purchase probabilities (right graph) for each ad condition. The results of all pairwise *t*-tests for the equality of means are reported in Table 1.

31% less effective at increasing searches ($\hat{\beta}_{genre} - \hat{\beta}_{plain} = -0.023$ with $p = 0.029$), whereas it makes the ad for *Stateline* directionally 15% more effective at increasing searches ($\hat{\beta}_{genre} - \hat{\beta}_{plain} = 0.011$ with $p = 0.334$). The effects on purchase probabilities are directionally the same but not statistically significant. By contrast, revealing price makes the ad more effective for both books. For *Lost Girls*, the price ad is 31% more effective at increasing searches ($\hat{\beta}_{price} - \hat{\beta}_{plain} = 0.022$ with $p = 0.054$) and 51% more effective at increasing purchases ($\hat{\beta}_{price} - \hat{\beta}_{plain} = 0.019$ with $p = 0.027$) than the plain ad. We find similar effects for *Stateline*, albeit with relatively high *p*-values. As these estimates suggest, revealing different book attributes in ads may substantially strengthen or weaken ad effects.

To understand the mechanisms behind these content effects, we turn to our theoretical predictions in Section 2. Consider first the effects of revealing genre. Our model rests on the assumption that consumers cannot infer genre from the book's title and cover art, and thus the genre ad reveals new information relative to the plain ad. To test whether this assumption holds, we look for evidence of differential search patterns in the plain ads condition. If consumers exposed to a plain ad can infer the advertised book's genre, then those who favor that genre should search the book more frequently than others. Column 1 in Table 2 shows mixed evidence. After being exposed to a plain ad for *Lost Girls*, consumers who favor romance novels have a lower baseline search rate

	Search Est.	Search S.E.	Search P-value	Purch. Est.	Purch. S.E.	Purch. P-value
ATE Regression Estimates (Lost Girls):						
β Plain ad	0.071	0.013	0.000	0.037	0.010	0.000
β Genre ad	0.049	0.012	0.000	0.031	0.009	0.001
β Price ad	0.093	0.013	0.000	0.056	0.010	0.000
Implied ATE differences:						
β Genre $-$ β Plain	-0.023	0.010	0.029	-0.006	0.008	0.480
β Price $-$ β Plain	0.022	0.011	0.054	0.019	0.009	0.027
β Price $-$ β Genre	0.045	0.011	0.000	0.025	0.009	0.004
ATE Regression Estimates (Stateline):						
β Plain ad	0.072	0.013	0.000	0.057	0.009	0.000
β Genre ad	0.083	0.013	0.000	0.064	0.009	0.000
β Price ad	0.087	0.013	0.000	0.068	0.009	0.000
Implied ATE differences:						
β Genre $-$ β Plain	0.011	0.011	0.334	0.007	0.009	0.432
β Price $-$ β Plain	0.014	0.011	0.197	0.011	0.009	0.213
β Price $-$ β Genre	0.004	0.011	0.750	0.004	0.009	0.649

Table 1: **Estimated advertising effects on searches and purchases.** The table reports ATE estimates on the search probability (columns 1-3) and purchase probability (columns 4-6) of the advertised book. For each outcome, we report the treatment effect estimates $\hat{\beta}_j$, robust standard errors, and p-values. The top panel reports the results for *Lost Girls*, in which rows 1-3 present the estimates $\hat{\beta}_{plain}$, $\hat{\beta}_{genre}$, and $\hat{\beta}_{price}$, and rows 4-6 report results from the pairwise t-tests of coefficients $\hat{\beta}$ where the null hypothesis assumes the two effects are equal. The bottom panel reproduces the same results for *Stateline*.

than others. However, after exposure to a plain ad for *Stateline*, consumers who prefer the mystery genre have a higher baseline search rate, suggesting they can partially infer this book's genre. Although this partial inference can weaken our experimental manipulation for *Stateline*, genre ads should still polarize consumers' search decisions as long as some consumers cannot infer genres from titles and book covers.

Proposition 2a predicts that genre ads may polarize consumers' search decisions relative to plain ads. Figure 4a provides a direct test of this proposition. The figure visualizes the average search rate of the advertised book under genre ads (red dashed line) and plain ads (blue solid line) for five groups of consumers who differ by their stated preference for the advertised genre. Consistent with the proposition, revealing genre increases the search probability among consumers

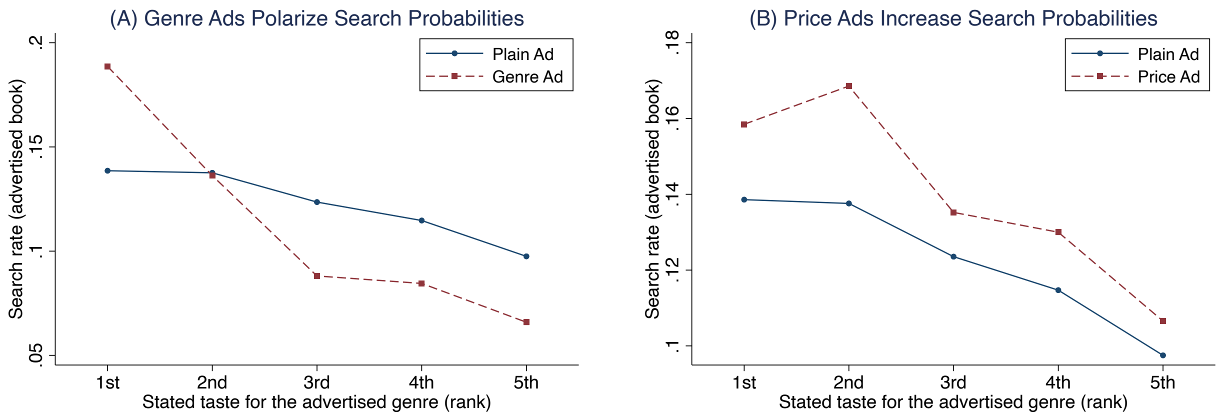


Figure 4: **The effects of genre and price ads on the search rate of the advertised book.** The left graph show the average search and purchase probabilities under genre ads and price ads. The right graph show the same probabilities but for price ads relative to plain ads. The effects are shown for five groups of consumers based on their self-reported preference for the genre of the book they saw advertised (i.e., either romance or mystery genre depending on whether they saw an ad for *Lost Girls* or *Stateline*). 1st is the most preferred genre and 5th is the least preferred. Both graphs pool data across the two books.

who favor this genre, has little effect on consumers who ranked this genre second, and substantially decreases the search probability among all other consumers.

We formally test these effects in Table 2 by estimating the ATE of genre ads on search and purchase probabilities relative to plain ads. To maximize statistical power, we pool consumers into two groups: those who ranked the advertised book's genre as their most preferred genre and everyone else. Panels A and B present results separately for each book, and in Panel C we pool data from both books. Focusing on the pooled estimates, we find that revealing genre significantly increases the search probability of the advertised book for consumers who favor its genre by $0.050/0.139 \approx 36\%$ ($p = 0.005$) and significantly decreases it by $0.024/0.118 \approx 20\%$ ($p = 0.003$) for all other consumers. We also show suggestive evidence that these effects translate into purchases: revealing genre increases the advertised book's purchase rate by $0.024/0.092 \approx 26\%$ ($p = 0.104$) for consumers who favor the advertised genre and decreases the purchase rate by $0.007/0.063 \approx 11\%$ among all others ($p = 0.245$).

This polarization result explains why revealing genre in *Stateline* ads increases the aggregate search probability but revealing genre in *Lost Girls* ads decreases it. As Proposition 2b shows,

	Plain Ad	Genre Ad	$\hat{\beta}$	S.E.	p-value
Panel A. Advertising for Lost Girls					
Prob. search Lost Girls:					
Consumers who ranked romance 1st	0.108	0.140	0.032	0.026	0.212
Consumers who ranked romance 2nd-5th	0.127	0.092	-0.035	0.011	0.002
Prob. buy Lost Girls:					
Consumers who ranked romance 1st	0.079	0.102	0.023	0.022	0.311
Consumers who ranked romance 2nd-5th	0.062	0.049	-0.013	0.008	0.133
Panel B. Advertising for Stateline					
Prob. search Stateline:					
Consumers who ranked mystery 1st	0.157	0.220	0.063	0.024	0.009
Consumers who ranked mystery 2nd-5th	0.108	0.097	-0.012	0.012	0.312
Prob. buy Stateline:					
Consumers who ranked mystery 1st	0.100	0.125	0.025	0.019	0.195
Consumers who ranked mystery 2nd-5th	0.065	0.063	-0.001	0.010	0.890
Panel C. Pooling Both Books					
Prob. search advertised book:					
Consumers who ranked ad genre 1st	0.139	0.189	0.050	0.018	0.005
Consumers who ranked ad genre 2nd-5th	0.118	0.094	-0.024	0.008	0.003
Prob. buy advertised book:					
Consumers who ranked ad genre 1st	0.092	0.116	0.024	0.015	0.104
Consumers who ranked ad genre 2nd-5th	0.063	0.056	-0.007	0.006	0.245

Table 2: **Match value effect of genre advertising.** The table reports our tests of the match value effect for *Lost Girls* (top panel), for *Stateline* (middle panel), and for both books with data pooled across all conditions (bottom panel). Each panel reports the means of the outcome variable in the two experimental conditions (columns 1-2), the estimated effect of revealing genre information relative to plain ads (column 3), and robust standard errors and p-values (columns 4-5). We split participants into two groups based on their stated genre preferences: participants who ranked the advertised genre first and all other participants.

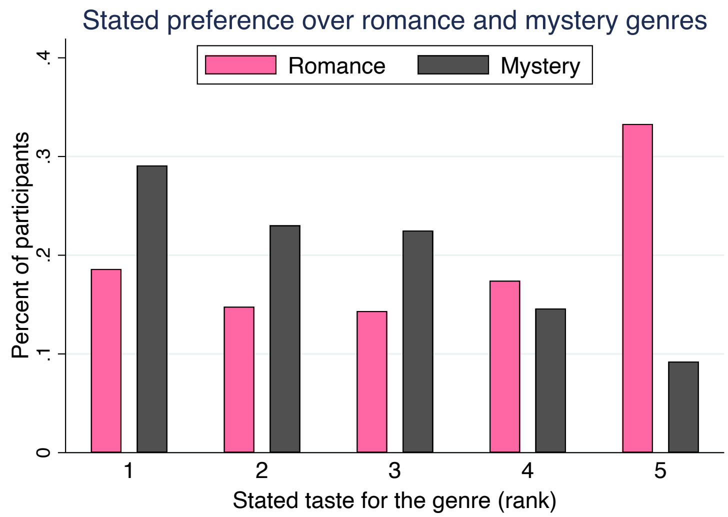


Figure 5: **Distribution of genre preferences for romance and mystery novels.** The graph shows the percent of respondents that assign a given rank to each genre. Rank 1 is the most preferred and rank 5 is the least preferred.

because revealing genre polarizes consumers' responses, the overall effectiveness of a genre ad depends on the share of consumers who favor the advertised genre. In our sample, consumers rank the mystery genre much higher on average than the romance genre (see Figure 5). For this reason, revealing the genre of a mystery book generates strong positive effects on searches that offset the negative effects on consumers who dislike the genre. By contrast, revealing the genre of a romance book generates mostly negative effects on search, which overpower the positive effects among the smaller group of consumers who like romance novels.

Next, to explain why price ads appear to be the most effective at driving searches and purchases, we turn to Proposition 3. Specifically, Proposition 3a posits that revealing price should increase the search and purchase probabilities of the advertised book for all consumers regardless of their genre preferences, assuming the revealed price is sufficiently appealing. The latter assumption holds in our experiment because price ads reveal the advertised book to be one of the cheapest options in the store.

To test this prediction, in Figure 4b we visualize the average search rate of the advertised book under price ads (red dashed line) and plain ads (blue solid line) for the same five consumer groups based on their stated genre preferences. Relative to plain ads, price ads increase the search probabilities in all consumer groups. We analyze these differences formally in Appendix Table A6. Consistent with Proposition 3a, the price ad directionally increases the search rate by $0.020/0.139 \approx 14\%$ ($p = 0.244$) among consumers who ranked the advertised genre first and by $0.017/0.118 \approx 14\%$ ($p = 0.059$) among all other consumers. Once again, these effects on search translate into purchases: revealing price directionally increases purchases among consumers who rate the advertised genre first $0.005/0.092 \approx 5\%$ ($p = 0.717$) and significantly increases purchases by $0.018/0.063 \approx 28\%$ ($p = 0.010$) among all other consumers.

These uniform responses explain why price ads are highly effective in our experiment. Consistent with Proposition 3a, a low price ad induces positive responses among all consumers regardless of their genre preferences, thus increasing the average search and purchase probabilities of the advertised book (Proposition 3b).

Put together, our experimental results show that ad content plays a substantial role in shaping advertising effects, and our theoretical model clarifies the mechanisms behind these content effects. When an ad reveals a favorable vertical attribute, such as a low price, the effects of ad content are positive across consumers with different genre preferences because all consumers positively update their beliefs about the book. By contrast, revealing a horizontal attribute, such as the book's genre, attracts some consumers while discouraging others from searching the book. Importantly, revealing a niche genre that few consumers like but many dislike significantly reduces searches and directionally reduces purchases of the advertised book.

5.4 Spillover Effects

We have so far discussed how ad content influences searches and purchases of the advertised book. In practice, advertising content effects might also spill over to non-advertised books. Although our search model does not directly predict these spillovers, the prior empirical literature has presented evidence that ad exposure increases demand for products that are similar to the advertised option

(Lewis and Nguyen, 2015; Sahni, 2016; Shapiro, 2018).[24] In the case of ad content, revealing an attribute in ads could make it more salient to consumers (Mackenzie, 1986), which may lead them to focus on other books with this attribute. Genre ads may then encourage consumers to seek other books of the same genre, and price ads may lead them to examine other cheap books offered in the store.

Both advertisers and platforms could benefit from knowing whether such spillovers occur. An advertiser, for example, may have little interest in revealing attributes in ads if it knows that doing so will increase demand for similar products sold by competitors. Further, a platform might want to understand whether price ads for individual products can make consumers more price-sensitive, thus changing the platform's pricing incentives.

In Table 3, we test for spillover effects using several outcome variables. First, if a price ad induces consumers to search other inexpensive books, consumers may sort books by price to locate other cheap options. In the same vein, if a genre ad encourages consumers to seek other books of the same genre, they may use filters to navigate to the relevant genre subcategory. We find null effects in both cases (p-values between 0.108 and 0.986). Second, even without inducing consumers to use different search tools, ad content could still make them more likely to click on the organic listings of similar books. We test for this effect but find little evidence that price ads increase the search or purchase probabilities of other inexpensive books priced below \$1 (p-values 0.599 and 0.723), or that genre ads induce consumers to search or purchase non-advertised books of the same genre (p-values 0.581 and 0.304). Lastly, consumers do not report ascribing more importance to price or genre after being exposed to ads that advertise these attributes (p-values 0.694 and 0.601).

Although we find no evidence of spillovers in the attribute space, we do find evidence of spatial spillovers.[25] As shown in Appendix Figure A6, advertising draws consumers' attention to books

[24] The literature on modeling cross-product spillovers in consumer search is still in its infancy (Malladi, 2022; Hodgson and Lewis, 2023), and we are not aware of any theoretical search model that micro-founds the advertising content spillovers we study.

[25] This analysis, as well as our analysis of how ads affect consumer's satisfaction with their selected books (see Section 5.5), are the only analyses we did not anticipate in the study pre-registration.

Pooling Both Books	Plain Ad	Attribute Ad	$\hat{\beta}$	S.E.	p-value
Panel A. Spillovers from price ads:					
Sorted by price low-to-high	0.233	0.230	-0.004	0.010	0.716
Sorted by price high-to-low	0.033	0.028	-0.005	0.004	0.205
Searched other cheap books	0.514	0.507	-0.006	0.012	0.599
Bought another cheap book	0.419	0.424	0.004	0.012	0.723
Self-reported price importance	3.029	3.042	0.013	0.032	0.694
Panel B. Spillovers from genre ads:					
Filtered to advertised genre	0.017	0.017	-0.000	0.003	0.986
Filtered to any genre	0.060	0.070	0.009	0.006	0.108
Searched other books of advertised genre	0.282	0.287	0.006	0.011	0.581
Bought another book of advertised genre	0.199	0.208	0.010	0.009	0.304
Self-reported genre importance	4.011	3.998	-0.013	0.024	0.601

Table 3: **Advertising spillovers to similar non-advertised books.** Each panel reports the estimated ATE of revealing an attribute (price in Panel A and genre in Panel B) on measures of attribute-oriented search and the search and purchase probabilities of books similar to the advertised option. The table compares consumer behavior under plain ads to that under attribute ads (either genre or price ads, depending on the panel). Each panel reports the means of the outcome variables in the plain ads condition and in either the genre or price ad condition (columns 1-2), the estimated effect of attribute ads relative to the plain ads condition (column 3), and robust standard errors and p-values (columns 4-5). The estimates are pooled across both books to maximize statistical power. Cheap books are defined as books priced below $1.

located near the advertising banner (the front page layout is shown in Figure 1). Ads reduce the purchase rates of the two books in the leftmost column (*Mrs. Kennedy and Me* and *Dead by Sunset*) and increase the purchase rates of several books located immediately under the advertising banner. These spatial spillovers arise consistently for all ad copies.[26] We speculate that consumers examine the product list page from top to bottom and from left to right, which generates natural position effects. The ad banner then disrupts the normal flow of search and weakens these position effects. This may explain why the two books in the leftmost column become less popular – these books would normally be the most salient. The advertising banner might draw attention away from these

[26] Seiler and Yao (2017) hypothesize that newspaper feature ads could generate spillovers to other categories that are nearby in the physical store, but they report precisely estimated null effects. Bairathi et al. (2022) hypothesize that adding an endorsement badge to a service on an online platform could generate spillovers to unendorsed services. In their experiment, they find negative spillovers for proximate listings and positive spillovers to listings located further from the sponsored listing. Simonov et al. (2023) document attention spillovers from news articles to ads embedded in the news article. By contrast, we show spillovers going in the opposite direction, from ads to website content.

books and toward books that are located near the banner itself. Appendix E discusses these results in more detail.

5.5 Effects on Search Intensity and Choice Satisfaction

Our results shed light on how ads with varied content influence consumers' search and purchase decisions. So far, however, we have been silent on whether any of these effects benefit consumers. Ads could save consumers time by reducing the number of books they need to examine before finding a good match, or they could divert consumers' search toward a low quality option and increase the amount of time needed to find a good book. The welfare effects of ads will also depend on whether the books consumers choose after seeing ads match their preferences better or worse than the books they would choose without ads. Understanding these effects might be of particular interest for platforms that want to know whether showing ads on their websites can improve the shopping experience and increase customer retention.

Although a complete welfare analysis is outside the scope of this paper, here we explore the effects of ads on several proxies for consumer welfare. Appendix Figure A12 visualizes the effects of different ads on measures of overall search effort. Relative to no ads, a plain ad leads consumers to search 10% fewer books (from 2.14 to 1.92, $p = 0.059$), reduces the probability of opening more than one product list page by 9% (from 0.712 to 0.646, $p = 0.003$), and directionally reduces shopping time by 2.3% (from 3.88 to 3.79 minutes, $p = 0.570$).[27] These results suggest that plain ads induce consumers to search less. As long as this reduction in search does not lead to decreased customer satisfaction, it could be welfare-enhancing.

Next, we test whether consumers exposed to plain ads are more or less satisfied with their final choices than those in the no ad condition. If consumers exposed to plain ads are more satisfied with their purchases, they should be more likely to keep their selected book instead of choosing the cash after the experiment. We find that exposure to a plain ad does not significantly change

[27] Fong (2017) similarly finds that targeted offers for an online store reduce the total search activity on the retailer's website.

the probability that consumers keep their selected book (from 0.615 to 0.614, $p = 0.966$). Thus, although plain ads help consumers make their choices with less search, they do not necessarily improve the quality of these choices.

Ad content may amplify both of these effects. Genre ads, for instance, may help consumers quickly find a book with a high match value, reducing the time they need to spend on search. Our data do not support this conjecture: relative to plain ads, attribute ads do not generate incremental effects on the number of searched books, number of opened product list pages, shopping time, or the probability of keeping the book (see Appendix Figure A12). These findings suggest that revealing product attributes in ad creatives does not save consumers time and does not change how satisfied consumers are with their final choices. We acknowledge, however, that the estimates presented in this section are noisy and that the decision of whether to keep the book after the study may not capture all facets of consumer satisfaction.[28]

6 Discussion

One takeaway from our experimental results is that advertisers should carefully choose which product attributes to reveal in ad copies. Our experiment shows that advertising the right attributes can get consumers interested to learn the remaining attributes, but highlighting the wrong ones can convince consumers that the product is not even worth examining. Therefore, it might be a good idea to avoid advertising attributes that are likely to induce polarized responses from consumers.

Managers may also benefit from jointly optimizing the content of their ads and the scope of their advertising campaigns. A manager designing a mass advertising campaign might want to focus on advertising vertical attributes and avoid revealing niche product attributes that appeal to few consumers but repel many others. Alternatively, the manager can design a targeted campaign that selectively reveals a horizontal attribute. Our analysis suggests that the gains from such targeting can be sizable. For example, based on our estimates, showing the genre ad to consumers

[28]We tested whether the average effects mask heterogeneity across consumers with different genre preferences but did not find significant differences in the total number of searches or propensities to keep the book after the study.

who favor mystery novels and the price ad to everyone else could increase the search probability of *Stateline* by 14% relative to showing the price ad to everyone. More generally, by highlighting the aspects of the product each consumer finds the most appealing, personalized ads could minimize negative ad content effects, thus increasing the ROI of advertising. The literature has documented that many firms successfully use consumer data for ad targeting (Johnson et al., 2017; Sahni et al., 2019; Wernerfelt et al., 2022). Our results suggest that firms might find it valuable to use such data for personalizing ad content as well.

We conjecture that ad content may also affect demand elasticities and thus have downstream consequences for firms' pricing decisions. Price ads allow consumers to screen the advertised book on price and may thus *rotate the book's demand curve counter-clockwise*, incentivizing the advertiser to charge a lower price (Robert and Stahl, 1993; Kaul and Wittink, 1995). By contrast, genre ads allow consumers to screen the advertised book based on how much they like the revealed genre, which may *rotate the book's demand curve clockwise* (Johnson and Myatt, 2006) and incentivize the advertiser to charge a higher price (Meurer and Stahl II, 1994). Our results show that consumers' responses to ad content are consistent with the theoretical predictions that lead to these demand rotations. A promising direction for future research would be to explicitly test for these rotations using data with exogenous variation in both ad content and prices.

Finally, we show that ad exposure reduces the total amount of search without affecting customers' satisfaction with their chosen book. This finding suggests an intriguing possibility that showing display ads on a platform might make shopping more efficient, which could potentially improve customer retention. Because we do not observe repeat store visits in our data, we leave testing this conjecture to future work.

7 Conclusions

In this paper, we create a simulated shopping environment in which consumers need to choose from an assortment of e-books while being exposed to display advertisements with varied content. Using data from an incentive-compatible experiment, we estimate how ad content causally influences consumer search and choice.

Although there are benefits to creating a simulated store, this approach is not without limitations. Relative to major online bookstores, our store lacks customer ratings and reviews, which could serve as an alternative source of information about products and thus reduce the effects of ad content. Further, our limited book assortment and forced-choice design could lead to larger than normal ad effects in our setting. For this reason, we caution against interpreting our results as capturing realistic magnitudes of ad effects in online retail.

Despite these limitations, we believe the methodology of creating a simulated online store holds promise. As our results show, it is possible to create a store where consumers make realistic search and purchase decisions and respond to ads. We have also demonstrated that one can conduct a large-scale lab experiment with thousands of participants by choosing a product that can be delivered online. Researchers can apply this methodology to other marketing problems, not necessarily related to ad content effects. Having created a simulated store, researchers can freely manipulate how the store presents information about products. Through such experiments, researchers could study how online retailers and platforms ought to optimally design the information environment in which consumers conduct their search. We would be excited to see future work in this area.

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References

ABERNETHY, A. M. AND G. R. FRANKE (1996): "The information content of advertising: A meta-analysis," *Journal of advertising*, 25, 1–17. 5

ACKERBERG, D. A. (2001): "Empirically distinguishing informative and prestige effects of advertising," *RAND Journal of Economics*, 316–333. 3

ANAND, B. N. AND R. SHACHAR (2011): "Advertising, the matchmaker," *The RAND Journal of Economics*, 42, 205–245. 3

ANDERSON, S. P., F. CILIBERTO, J. LIAUKONYTE, AND R. RENAULT (2016): "Push-me pull-you: comparative advertising in the OTC analgesics industry," *The RAND Journal of Economics*, 47, 1029–1056. 1

ANDERSON, S. P. AND R. RENAULT (2006): "Advertising content," *American Economic Review*, 96, 93–113. 4

ARBATSKAYA, M. (2007): "Ordered search," *The RAND Journal of Economics*, 38, 119–126. 1, 13

ARMSTRONG, M., J. VICKERS, AND J. ZHOU (2009): "Prominence and consumer search," *The RAND Journal of Economics*, 40, 209–233. 1, 13

BAIRATHI, M., X. ZHANG, AND A. LAMBRECHT (2022): "The value of platform endorsement," *Available at SSRN 4144605*. 26

BERTRAND, M., D. KARLAN, S. MULLAINATHAN, E. SHAFIR, AND J. ZINMAN (2010): "What's advertising content worth? Evidence from a consumer credit marketing field experiment," *The quarterly journal of economics*, 125, 263–306. 1

BISWAS, S. (2020): "Investigating the effects of including discount information in advertising," Ph.D. thesis, The University of Chicago. 1

BRUCE, N. I., M. BECKER, AND W. REINARTZ (2020): "Communicating brands in television advertising," *Journal of Marketing Research*, 57, 236–256. 1

BRUHN, M. AND D. MCKENZIE (2009): "In pursuit of balance: Randomization in practice in development field experiments," *American economic journal: applied economics*, 1, 200–232. 22

CHANDY, R. K., G. J. TELLIS, D. J. MACINNIS, AND P. THAIVANICH (2001): "What to say when: Advertising appeals in evolving markets," *Journal of marketing Research*, 38, 399–414. 1

CHIOU, L. AND C. TUCKER (2022): "How Do Restrictions on Advertising Affect Consumer Search?" *Management Science*, 68, 866–882. 1

DALL'OLIO, F. AND D. VAKRATSAS (2023): "The impact of advertising creative strategy on advertising elasticity," *Journal of Marketing*, 87, 26–44. 1

DANG, C., R. URSU, AND P. CHINTAGUNTA (2022): "Product Revisits and Consumer Consideration Sets," *SSRN 920693*. 8

DU, R. Y., L. XU, AND K. C. WILBUR (2019): "Immediate responses of online brand search and price search to TV ads," *Journal of Marketing*, 83, 81–100. 1

DUFLO, E., R. GLENNERSTER, AND M. KREMER (2007): "Using randomization in development economics research: A toolkit," *Handbook of development economics*, 4, 3895–3962. 22

FONG, N. M. (2017): "How targeting affects customer search: A field experiment," *Management Science*, 63, 2353–2364. 1, 7, 27

GABAIX, X., D. LAIBSON, G. MOLOCHE, AND S. WEINBERG (2006): "Costly information acquisition: Experimental analysis of a boundedly rational model," *American Economic Review*, 96, 1043–1068. 1

GOSSNER, O., J. STEINER, AND C. STEWART (2021): "Attention please!" *Econometrica*, 89, 1717–1751. 4

GREMINGER, R. P. (2022): "Optimal search and discovery," *Management Science*, 68, 3904–3924. 2.1, A

GROSSMAN, G. M. AND C. SHAPIRO (1984): "Informative advertising with differentiated products," *The Review of Economic Studies*, 51, 63–81. 15

GUITART, I. A. AND S. STREMERSCH (2021): "The Impact of Informational and Emotional Television Ad Content on Online Search and Sales," *Journal of Marketing Research*, 58. 1

HAAN, M. A. AND J. L. MORAGA-GONZÁLEZ (2011): "Advertising for attention in a consumer search model," *The Economic Journal*, 121, 552–579. 1, 13

HARTNETT, N., R. KENNEDY, B. SHARP, AND L. GREENACRE (2016): "Creative that sells: How advertising execution affects sales," *Journal of Advertising*, 45, 102–112. 1

HODGSON, C. AND G. LEWIS (2023): "You can lead a horse to water: Spatial learning and path dependence in consumer search," Tech. rep., National Bureau of Economic Research. 24

HONKA, E., A. HORTAÇSU, AND M. A. VITORINO (2017): "Advertising, consumer awareness, and choice: Evidence from the US banking industry," *The RAND Journal of Economics*, 48, 611–646. 1, 2.2

IMBENS, G. W. (2010): "Better LATE than nothing: Some comments on Deaton (2009) and Heckman and Urzua (2009)," *Journal of Economic literature*, 48, 399–423. 5.1

JANSSEN, M. C. AND M. C. NON (2008): "Advertising and consumer search in a duopoly model," *International Journal of Industrial Organization*, 26, 354–371. 13

JOHNSON, G. A., R. A. LEWIS, AND E. I. NUBBEMEYER (2017): "Ghost ads: Improving the economics of measuring online ad effectiveness," *Journal of Marketing Research*, 54, 867–884. 6

JOHNSON, J. P. AND D. P. MYATT (2006): "On the simple economics of advertising, marketing, and product design," *American Economic Review*, 96, 756–784. 4, 6

KALYANAM, K. AND Y. KIM (2024): "Ad content and consumer engagement: Theory and evidence from a field experiment," *Working paper*. 7

KAUL, A. AND D. R. WITTINK (1995): "Empirical generalizations about the impact of advertising on price sensitivity and price," *Marketing Science*, 14, G151–G160. 6

LEE, D., K. HOSANAGAR, AND H. S. NAIR (2018): "Advertising content and consumer engagement on social media: Evidence from Facebook," *Management Science*, 64, 5105–5131. 1

LEWIS, R. AND D. NGUYEN (2015): "Display advertising's competitive spillovers to consumer search," *Quantitative Marketing and Economics*, 13, 93–115. 5.4

LIAUKONYTE, J., T. TEIXEIRA, AND K. C. WILBUR (2015): "Television advertising and online shopping," *Marketing Science*, 34, 311–330. 1

LODISH, L. M., M. ABRAHAM, S. KALMENSON, J. LIVELSBERGER, B. LUBETKIN, B. RICHARDSON, AND M. E. STEVENS (1995): "How TV advertising works: A meta-analysis of 389 real world split cable TV advertising experiments," *Journal of Marketing Research*, 32, 125–139. 1

MACINNIS, D. J., A. RAO, AND A. WEISS (2002): "Assessing when increased media weight of real-world advertisements helps sales," *Journal of Marketing Research*, 39, 391–407. 1

MACKENZIE, S. B. (1986): "The Role of Attention in Mediating the Effect of Advertising on Attribute Importance," *Journal of consumer research*, 13, 174–195. 5.4

MALLADI, S. (2022): "Searching in the Dark and Learning Where to Look," *Available at SSRN 4084113*. 24

META (2017): "The results are in: High-quality creative increases ad ROI," *https://www.facebook.com/business/news/insights/high-quality-creative-increases-ad-roi*. 1

MEURER, M. AND D. O. STAHL II (1994): "Informative advertising and product match," *International Journal of Industrial Organization*, 12, 1–19. 15, 6

MILGROM, P. AND J. ROBERTS (1986): "Price and advertising signals of product quality," *Journal of political economy*, 94, 796–821. 1, 14

NELSON, P. (1974): "Advertising as information," *Journal of political economy*, 82, 729–754. 1, 14

NIELSEN (2022): "When It Comes to Advertising Effectiveness, What Is Key? (accessed July 21, 2023)," *https://www.nielsen.com/us/en/insights/article/2017/when-it-comes-to-advertising-effectiveness-what-is-key*. 1

RESNIK, A. AND B. L. STERN (1977): "An analysis of information content in television advertising," *Journal of marketing*, 41, 50–53. 5

REUTSKAJA, E., R. NAGEL, C. F. CAMERER, AND A. RANGEL (2011): "Search dynamics in consumer choice under time pressure: An eye-tracking study," *American Economic Review*, 101, 900–926. 1

ROBERT, J. AND D. O. STAHL (1993): "Informative price advertising in a sequential search model," *Econometrica: Journal of the Econometric Society*, 657–686. 6

SAHNI, N. S. (2016): "Advertising spillovers: Evidence from online field experiments and implications for returns on advertising," *Journal of Marketing Research*, 53, 459–478. 5.4

SAHNI, N. S., S. NARAYANAN, AND K. KALYANAM (2019): "An experimental investigation of the effects of retargeted advertising: The role of frequency and timing," *Journal of Marketing Research*, 56, 401–418. 6

SEILER, S. AND S. YAO (2017): "The impact of advertising along the conversion funnel," *Quantitative Marketing and Economics*, 15, 241–278. 26

SHAPIRO, B. T. (2018): "Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants," *Journal of political economy*, 126, 381–437. 5.4

SHI, S. W., M. WEDEL, AND F. PIETERS (2013): "Information acquisition during online decision making: A model-based exploration using eye-tracking data," *Management Science*, 59, 1009–1026. 1

SIMONOV, A., T. VALLETTI, AND A. VEIGA (2023): "Attention Spillovers from News to Ads: Evidence from an Eye-Tracking Experiment," *Working Paper*. 26

STERN, B. L. AND A. J. RESNIK (1991): "Information content in television advertising: A replication and extension." *Journal of Advertising Research*. 5

STEWART, D. W. AND D. H. FURSE (1986): *Effective television advertising: A study of 1000 commercials*, Lexington, MA: Lexington Books. 1

SUDHIR, K., S. ROY, AND M. CHERIAN (2016): "Do sympathy biases induce charitable giving? The effects of advertising content," *Marketing Science*, 35, 849–869. 6

TSAI, Y.-L. AND E. HONKA (2021): "Informational and Noninformational Advertising Content," *Marketing Science*, 40, 1030–1058. 1

URSU, R., A. SIMONOV, AND E. AN (2021a): "Online Advertising as Passive Search," *Available at SSRN 3841266*. 1, 2.2

URSU, R., Q. P. ZHANG, AND T. ERDEM (2021b): "Prior Information and Consumer Search: Evidence from Eye-tracking," *NYU Stern School of Business Forthcoming*. 1

WERNERFELT, N., A. TUCHMAN, B. SHAPIRO, AND R. MOAKLER (2022): "Estimating the value of offsite data to advertisers on meta," *University of Chicago, Becker Friedman Institute for Economics Working Paper*. 6

WLÖMERT, N. AND F. EGGERS (2016): "Predicting new service adoption with conjoint analysis: External validity of BDM-based incentive-aligned and dual-response choice designs," *Marketing Letters*, 27, 195–210. 19

XU, L., K. C. WILBUR, S. SIDDARTH, AND J. M. SILVA-RISSO (2014): "Price Advertising by Manufacturers and Dealers," *Management Science*, 60, 2816–2834. 6

Online Appendix

A Proofs

Proof of Proposition 1. By the "eventual purchases" theorem in Greminger (2022, p.3912), the purchase outcome of a consumer i is equivalent to purchasing a book j with the highest *effective value* w_{ij}. In the case without ads, this value is defined as $w_{ij}^N = \min(u_{ij}, z_{s,ij}^N, z_{d,ij} + \omega \cdot \min(u_{ij}, z_{s,ij}^N))$ for $j \notin S_0$ and $w_{ij}^N = \min(u_{ij}, z_{s,ij}^N)$ for $j \in S_0$, where $z_{s,ij}^N$ is book j's search value, $z_{d,ij} = -\alpha_i \bar{p} + \Xi_{ij}(c_s, c_d^{l(j)})$ is this book's discovery value, $c_d^{l(j)}$ is the discovery cost for book j on list page $l(j)$, $\Xi_{ij}(c_s, c_d^{l(j)})$ is a decreasing function in $c_d^{l(j)}$, and ω is an infinitesimal number .[29] After a plain ad exposure, the effective value of the advertised book k becomes $w_{ik}^A = \min(u_{ik}, z_{s,ik}^A)$ where $z_{s,ik}^A$ is the new search value. Let $M_{s,k}$ and $M_{p,k}$ denote the mass of consumers searching and purchasing book j. Because $\Xi_{ik}(c_s, c_d^{l(k)})$ decreases in $c_d^{l(k)}$, then $\exists \tilde{c}_d$ so that $w_{ik}^A > w_{ik}^N$ if $c_d^{l(k)} > \tilde{c}_d$ for any taste profile (α_i, γ_i). In this case, we have $w_{im}^N = w_{im}^A$ for $\forall m \neq k$ and $w_{ik}^N < w_{ik}^A$, which implies $M_{p,k}^A > M_{p,k}^N$. Further, because $c_d^{l(k)} \to \infty$ implies $M_{s,k} \to 0$, there exists $\hat{c}_d$ so that $M_{s,k}^A > M_{s,k}^N$ if $c_d^{l(k)} > \hat{c}_d$. Combining these two results establishes Proposition 1 if we set $c_d^* = \max(\hat{c}_d, \tilde{c}_d)$ and assume $c_d^{l(k)} \geq c_d^*$.

Proof of Proposition 2. The effective utility of consumer i for the advertised book k is $w_{ik}^A = \min(u_{ik}, z_{s,ik}^A)$ under the plain ad and $w_{ik}^G = \min(u_{ik}, z_{s,ik}^G)$ under the genre ad, where $z_{s,ik}^A$ and $z_{s,ik}^G$ are the search values. Under the plain ad, consumer i with taste profile (α_i, γ_i) expects u_{ik} to be distributed with CDF $F_u^A(u; \alpha_i, \gamma_i) = Pr(-\alpha_i p_k + \gamma_i g_j + \varepsilon_{ik} < u)$, whereas under the genre ad this CDF is given by $F_u^G(u|g_j = 1; \alpha_i, \gamma_i) = Pr(-\alpha_i p + \gamma_i + \varepsilon_{ik} < u)$. If $\gamma_i > 0$, then $F_u^G(u|p; \alpha_i, \gamma_i) < F_u^A(u; \alpha_i, \gamma_i)$, so the distribution of utilities under the genre ad first-order stochastically dominates that under the plain ad. Thus, we have $z_{s,ik}^G > z_{s,ik}^A$ for any price sensitivity α_i, and therefore the

[29] Greminger defines the search value $z_{s,ij}^N$ as the hypothetical utility in hand that makes consumer i indifferent between searching it at cost c_s and not searching it (the superscript "N" stands for "No Ads"). In turn, $z_{d,ij}$ is the discovery value of book j, defined as the hypothetical utility in hand that makes consumer i indifferent between discovering it at cost $c_d^{l(j)}$ and not discovering it, where $l(j)$ denotes the product list page where the book resides. Finally, $\Xi_{ji}(c_s, c_d^{l(j)})$ is a decreasing function in $c_d^{l(j)}$ defined in equation (10) of his paper.

probabilities that consumer i searches and purchases book j both increase. If $\gamma_i < 0$ then similarly $F_u^G(u|p;\gamma_i) > F_u^A(u;\gamma_i)$ and $z_{s,ik}^G < z_{s,ik}^A$ for any price sensitivity α_i, so the search and purchase probabilities for book j decrease. Finally, if $\gamma_i = 0$ then $w_{ik}^G = w_{ik}^A$ and the search and purchase probabilities of the consumer do not change. Combining these results, we get that $\exists \bar{f} \in (0,1)$ such that $M_{s,k}^G > M_{s,k}^A$ and $M_{p,k}^G > M_{p,k}^A$ if $Pr(\gamma_i > 0) > \bar{f}$. Moreover, it also holds that $\exists \check{f} \in (0,1)$ such that the effect is reversed if $Pr(\gamma_i < 0) > \check{f}$. In that case, we have $M_{s,k}^G < M_{s,k}^A$ and $M_{p,k}^G < M_{p,k}^A$.

Proof of Proposition 3. Using the same arguments as in Proposition 2, we get $w_{ik}^A = \min(u_{ik}, z_{s,ik}^A)$ under the plain ad and $w_{ik}^P = \min(u_{ik}, z_{s,ik}^P)$ under the price ad. The consumer expects the utility u_{ik} to be distributed with CDF $F_u^A(u;\alpha_i,\gamma_i) = Pr(-\alpha_i p_j + \gamma_i g_j + \varepsilon_{ik} < u)$, under the plain ad and $F_u^P(u|p;\alpha_i,\gamma_i) = Pr(-\alpha_i p + \gamma_i g_j + \varepsilon_{ik} < u|p = p_j)$ under the price ad. When $p_k = p^{max}$ then $F_u^P(u|p;\alpha_i,\gamma_i) > F_u^A(u;\alpha_i,\gamma_i)$ so the utility distribution under the plain ad stochastically dominates that under the price ad. This implies $z_{s,ik}^P < z_{s,ik}^A$, which leads to a lower probability of searching and purchasing book k for any taste profile (α_i,γ_i). In turn, if $p_k = 0$ then $F_u^P(u|p;\alpha_i,\gamma_i) < F_u^A(u;\alpha_i,\gamma_i)$ and $z_{s,k}^P > z_{s,k}^A$ for any taste profile (α_i,γ_i). By continuity, $\exists \tilde{p}$ such that $M_{s,k}^P > M_{s,k}^A$ and $M_{p,k}^P > M_{p,k}^A$ if $p_k < \tilde{p}$.

B Additional Implementation Details

B.1 Bookstore Design and Consumer Tracking

We create a bookstore using open-source website development software, WordPress, which is commonly used for creating e-commerce stores. We augment the standard functionality of WordPress with a plug-in "WooCommerce" that allows us to create a realistic storefront, customize the store layout, populate the store with a custom assortment of books (see Section 3.2), and create a checkout page. To randomize ad exposures, we also use plug-ins that enable us to personalize the store layout for each website visitor.

Lastly, by connecting our WordPress account to Google Analytics, we collect anonymized individual-level data that capture everything website visitors see and do when browsing our bookstore. The default Google Analytics software tracks basic events like clicks and add-to-cart events, logging them with corresponding time stamps. We augment these data by creating custom event tags that document consumer search at a more granular level.[30] With these custom tags, we track how far down a person scrolls in the product list; the number of product list pages they open; whether they use filters, sorting tools, or search queries; whether they click on the advertising banner; and even whether they open several tabs in their browser while comparing books. We also observe the order in which books are presented to each user in the default sort, on product list pages after applying filters or using search queries, and in recommendation panels. To verify the quality of collected data, we browse the store according to a pre-determined script and verify that the resulting dataset accurately reflects the scripted browsing activity (see the Online Supplement for details).

B.2 Book Assortment Selection

We populate our bookstore with an assortment of 100 strategically selected books. We describe our book selection criteria below. Our store should offer a reasonably large assortment of differentiated options to create a meaningful search problem. To this end, we include books from five different genres: biography/memoir, fantasy, mystery/thriller, romance, and science fiction. By including books of different genres, we make sure the store offers appealing options for users with heterogeneous preferences.

We also want to select high-quality books to interest users in making a purchase and keeping the book after the study. However, we do not want any particular book to dominate other options. To achieve this balance, we scrape genre-specific bestseller lists from Amazon and construct a list of the 300 most popular books within each genre. For each genre, we then discard the top 50 and select 20 books that are currently sold at a price below $3, which helps us reduce the expected cost

[30]To further improve this methodology, researchers can employ state of the art tracking tools such as screen recordings and heat maps offered in commercial analytics software (e.g., Hotjar, Mouseflow, or Contentsquare).

of the experiment. Choosing inexpensive books also reduces the dispersion of prices in the store, thus making it more likely that no single book dominates other options.

We set the books' prices equal to the current Amazon prices, which range between \$0.99 and \$2.99, except for the two advertised books that we sell at \$0.99 instead of the original \$2.99. Section 3.3 explains how we choose the books to advertise and our reasons for changing their prices. The average price of books in our assortment is \$2.09. Finally, in the default sorting of the product list, each page displays two books from each genre, ordering books within each genre by their Amazon sales rank. In our store, we keep prices and rankings fixed over time, even when the actual prices and sales ranks of these books change on Amazon. In the Online Supplement, we report the full list of 100 books in the assortment along with their prices and rankings.

B.3 Additional Details on Timeline and Sample Selection

We recruited participants from Amazon Mechanical Turk (MTurk). In all studies, we used Cloud Research, a platform that facilitates the recruiting of MTurk workers for academic and industry research. First, to stress-test our experiment infrastructure, we ran a pilot experiment on February 1-3, 2022. This study was a simplified experiment with only $N = 692$ participants and one advertising banner instead of six. Based on the results of this pilot experiment, we selected a compensation scheme that allows us to incentivize realistic choices while also minimizing the cost of the experiment (see Section 4.2 for details). Specifically, during the pilot experiment we randomly assigned all participants to four incentive conditions: 0% fulfillment (no one gets an e-book or a bonus), 10% lottery, 50% lottery, and 100% fulfillment (all participants receive an e-book and a bonus). We found that 50% is the lowest fulfillment probability that enables us to measure advertising effects similar to those in the fully incentivized 100% fulfillment condition. Based on the results of this study, we fixed the lottery probability at 50% in the main experiment.

Second, between March 30, 2022, and April 23, 2022, we conducted a pre-test of our main experiment with $N = 1,191$ participants. The data from this pre-test were used to obtain preliminary estimates of advertising effects, which served as inputs into our power calculations.

Finally, we pre-registered our main experiment on AsPredicted.org on May 18, 2022, and we ran it between May 19, 2022, and August 3, 2022. Based on the pre-test data, we calculated that we would need at least 12,500 participants to measure the effects of advertising exposure and content. Because our budget was fully determined by an external grant, we committed to running the study until we exhausted all available resources or ran out of participants to recruit on Amazon MTurk–whichever happened sooner (see the pre-registration document). In the end, we were able to collect survey responses from $N = 16,088$ participants before we exhausted our budget, out of which $N = 11,498$ participants (71.5%) had complete browsing and purchase data.

B.4 Pre-Experiment Survey

Participants were told that the study would investigate their preferences for e-books. We informed prospective participants that they would receive baseline compensation of $1.50 and that they might be eligible for an additional cash bonus of up to $3.00. To ensure they did not know the true purpose of the study, we did not mention advertising in the recruitment materials. We informed all participants that they must complete the survey using a standard browser (e.g., Chrome, Firefox, or Safari). Our goal was to minimize the number of participants who use privacy-focused browsers, such as Brave and Avast, which actively block user-tracking software. Importantly, before the study, we did not explicitly mention anything about behavior tracking to participants, as we did not want to alert them to the fact that their browsing behavior would be monitored. We also contemplated asking participants to turn off their ad blockers but decided against it for fear of artificially drawing attention to advertisements.

B.5 Randomization Algorithm

Our experiment randomizes participants into seven advertising conditions that determine which advertising banner the participant sees on the front page of the bookstore. We ran the main experiment between May 19, 2022, and August 3, 2022. During the first part of the experiment, between May 19, 2022, and July 5, 2022, we implemented randomization in the bookstore by using a paid plug-in called "A/B Testing" for WooCommerce. The plug-in served random advertisements to all website visitors, assigning each user to one of the seven experimental conditions according to the pre-specified probabilities. The plug-in tracked individual users over time with cookies so that users would not be re-randomized into another condition when they returned to the front page. While this randomization method worked well and passed all our quality tests (see the Online Supplement for details regarding these tests), we later realized that this method has a drawback. Specifically, because participants who used ad blockers or privacy browsers were not generating any search data, we could not observe which experimental conditions they were assigned to. Moreover, we suspected that ad blockers were more active at blocking Google Analytics in the treatment arms than in the control group. While this issue did not seem to affect our randomization checks, we confirmed this suspicion by browsing the website while using different ad blockers and checking the data gathered by Google Analytics.

To address this issue of missing data, we paused the experiment on July 5 and re-designed our randomization algorithm. In particular, we removed the A/B testing plug-in from the bookstore and instead performed randomization in the Qualtrics survey before sending participants to the bookstore. Operationally, this randomization system worked as follows. At the start of the Qualtrics survey, we assigned each participant to one of the seven experimental conditions according to the same pre-specified probabilities as before. We then gave each user a seven-digit code, e.g., "1BG83WL," in which the first symbol "1" reflects the experimental assignment and the remaining text "BG83WL" is a unique combination of alphanumeric symbols drawn without replacement. The user was then instructed to use their seven-digit code in the bookstore, both at the entry gate and at checkout.[31] Using the "If-So" plug-in for WooCommerce, we then served users their assigned advertisements based on the first digit of the seven-digit code they used at the entry gate. The advantage of this new randomization algorithm was that we knew users' experimental assignments even when they used ad blockers and privacy browsers because users were

[31] Because we randomly generated 7-digit alphanumeric codes, it was difficult for participants to cheat by guessing another valid unique code and buying another book. Even if they managed to do so, we would detect fraud because both book orders would be registered from the same IP address, which we would observe in the Google Analytics dataset.

randomized before they visited the store. We resumed the study with this new randomization and ran it between July 13, 2022, and August 3, 2022. We recruited about 60% of our total sample of participants under the first randomization algorithm and the remaining 40% under the second algorithm.

B.6 Order Fulfillment

As detailed in Section 4.2, we conducted a lottery in which each participant had a 50% chance of having their order fulfilled, which meant receiving their selected book as well as a monetary bonus. The easiest way to implement this incentive would be to recruit all participants, consolidate data on their book selections, and fulfill all orders at once. This timing was infeasible, however, because Amazon MTurk workers typically expect to receive their bonus compensation within a few days after taking the study. We could not, therefore, wait until the end of our three-month recruitment period. We solved this problem by fulfilling orders in one-week "waves." Each week, we made a list of book selections made by the participants who took the study in the previous seven days. We then conducted a lottery, selected the winners, manually purchased the books on Amazon, and sent the personalized redemption links to participants via the Amazon Mechanical Turk API. We also sent participants their personalized bonuses at that time. To avoid being flagged by Amazon for suspicious activity, we purchased all books using an Amazon Business Account affiliated with our university.[32] When participants received redemption links, they were told that they would have two weeks to redeem their books. After two weeks, we logged which books were still unredeemed and returned any unclaimed books for a full refund from Amazon.

[32]Prior to using the business account, we tried using one of our individual Amazon accounts. The account was immediately blocked by Amazon's anti-fraud algorithm after we purchased more than 300 books. We caution researchers against using their individual accounts for purchasing large numbers of products without special authorization of the online retailer.

B.7 Merging Datasets from Qualtrics and Google Analytics

Ideally, each person would participate in our study only once, answer all pre-experiment questions in the Qualtrics survey, use the code we assigned them to check out exactly one book, and return to the Qualtrics survey to answer all post-survey questions. Despite our best efforts to enforce these rules, some people attempted to fill out the survey multiple times or returned to the bookstore after the study to try to purchase another e-book. In this section, we discuss how we processed raw data to make sure these attempts to "game the system" did not contaminate our main experimental sample.

When constructing the main sample for estimation, we applied the following selection criteria. First, when we saw the same person attempting the Qualtrics survey multiple times, we only considered the first "successful" attempt and ignored any subsequent attempts. We call an attempt successful if the person passed the comprehension checks, was assigned a unique code, and used this code at the entry gate of our bookstore. To verify the code usage, we searched in the Google Analytics data (search data) for a user that entered this unique code at the entry gate during the "appropriate" time period, i.e., between the time when the survey attempt was started and finished according to Qualtrics. Given this selection rule, a person who took the survey once but did not pass comprehension checks was removed from the dataset. A person who failed comprehension checks the first time but then returned and passed them the second time was included in the dataset as long as they used their unique code in the bookstore on the second attempt. If the same person returned to the bookstore again, their third visit was excluded; in this case, we kept only their second visit in the data.

An exception to this rule are the participants who answered all pre-shopping and post-shopping questions in Qualtrics, but whose codes were not recorded within the Google Analytics data. This scenario could occur if a person completed the entire study but used an ad blocker that prevented us from collecting their browsing data.[33] Because we have no way of matching these participants

[33] It is not possible to "speed run" the study by completely skipping the bookstore. Upon checkout, the store generates a password that the participant has to enter in Qualtrics in order to access the remaining questions and complete the study. Therefore, a participant who attempts to skip the bookstore would realize that they do not have

to their search data, we dropped these survey attempts from the data.

We chose this data matching and cleaning process to ensure that we only include data from search sessions in which participants were exposed to advertising for the first time. In the final dataset, we observe a cross-section of participants and the time periods during which these participants took their first "successful" survey attempts. Using the assigned unique checkout codes, we merge Qualtrics data from these participants with individual-level search data from Google Analytics.[34] For each individual, we only retrieved search data for the appropriate period between the start and the end of the relevant survey attempt. Therefore, if a website user returned to our bookstore after the study trying to check out another book, their browsing activity after the experiment was dropped from the dataset.

C Sample Demographics and Randomization Checks

To check whether randomization appears to have been implemented properly, we tested for equality of means using demographic variables and stated book preferences collected before the randomization occurred. Figure A1 reports the distribution of preference rankings for different genres and Table A1 reports the average values of pre-treatment covariates across all participants in the main experiment.

Some participants were assigned to a treatment condition but either i) did not complete the check-out process, ii) did not return to the Qualtrics survey after checking out, or iii) used a privacy-preserving tool that prevents us from collecting their browsing data. While some attrition is expected, differential attrition across treatment groups could generate bias. We test for differential attrition using a sample of $7,479$ participants who took the study after July 13, 2022. As described in Appendix B.5, on that date we switched to a different randomization procedure that

the password they need to proceed.

[34] After checkout, we gave each participant a password that corresponds to the book they purchased (e.g., password "state303" for the book *Stateline*). We asked them to return to the Qualtrics survey and use the password to access additional questions. Thus, even if a participant did not generate any search data (e.g., due to a privacy-enhancing browser), we knew which book they purchased from the password they entered.

recorded experimental assignments before participants visited the bookstore. Because we observe the treatment assignments of all participants, including those that were eventually excluded from the sample, we can conduct a formal attrition analysis. We unfortunately cannot perform the same test for participants recruited prior to July 13 because we do not always observe their treatment assignments.

Using these data, we estimate the following regression:

$$\text{Completed Survey}_i = \alpha + \sum_{j=1}^{6} \beta_j \cdot T_i^j + \varepsilon_i \tag{1}$$

where α is the mean attrition rate in the no advertising condition and T_i^j is an indicator that participant i is assigned to the advertising condition j. The results are reported in Table A2. None of the ad conditions have significantly different attrition rates from the control group at the 5% significance level. We also cannot reject the hypothesis that all six ad conditions have the same attrition probability as the no advertising condition (joint $F = 1.64$ with p-value $= 0.132$).

Finally, Table A3 reports a balance test, showing the averages of all pre-treatment covariates across the seven experimental conditions, as well as the p-values of joint significance F-tests. While there are some minor differences in the averages of pre-treatment covariates across groups, we cannot reject the null hypothesis of equal means for 23 out of 24 covariates. One exception is that participants assigned to the no-advertising group are about 7 months older than participants assigned to the advertising conditions. Although the difference is significant at the 10% level, the difference appears economically small. We also simultaneously tested the null hypothesis of equal means for all 24 covariates by estimating a system of seemingly unrelated regressions (SUR), which generates a joint significance F-statistic with a high p-value of 0.289.

These results confirm that our experiment successfully randomized participants into advertising conditions. Given the slight imbalances across groups in Table A3, we also report robustness analyses in which we re-estimate all key advertising effects by controlling for pre-treatment covariates (see Tables A7-A10).

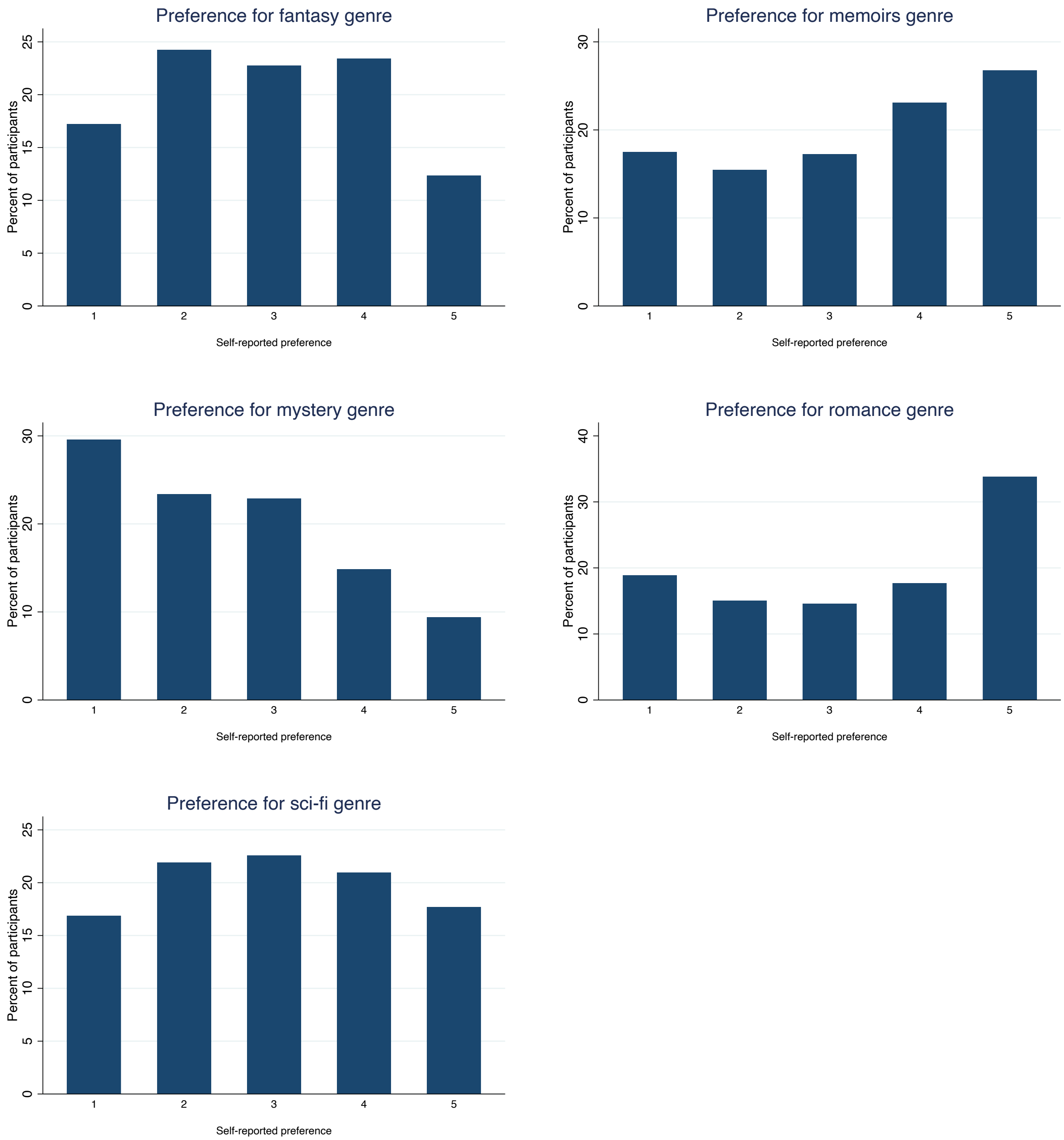
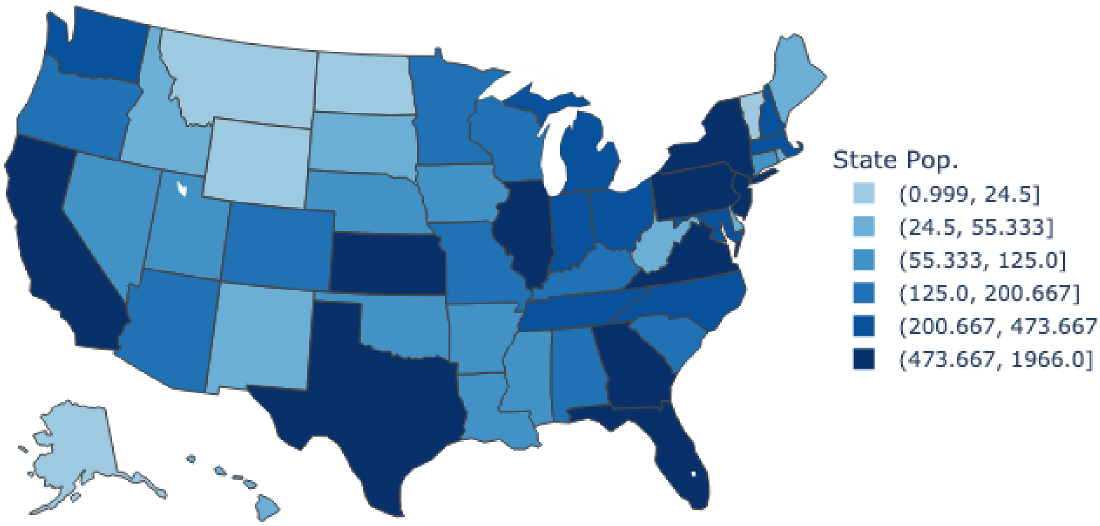


Figure A1: **Book genre preferences of consumers.**

	Mean	Std.dev	Min	P5	P50	P95	Max
Ranked fantasy genre (1-5)	2.89	1.28	1.0	1.0	3.0	5.0	5.0
Ranked mystery genre (1-5)	2.51	1.30	1.0	1.0	2.0	5.0	5.0
Ranked romance genre (1-5)	3.33	1.53	1.0	1.0	4.0	5.0	5.0
Ranked sci-fi genre (1-5)	3.01	1.35	1.0	1.0	3.0	5.0	5.0
Ranked memoirs genre (1-5)	3.26	1.44	1.0	1.0	3.0	5.0	5.0
Reads books per month	1.67	1.13	0.0	0.0	2.0	4.0	4.0
Reads e-books per month	1.99	1.27	0.0	0.0	2.0	4.0	4.0
Female	0.59	0.49	0.0	0.0	1.0	1.0	1.0
Black	0.10	0.30	0.0	0.0	0.0	1.0	1.0
Hispanic	0.06	0.24	0.0	0.0	0.0	1.0	1.0
Asian	0.04	0.20	0.0	0.0	0.0	0.0	1.0
Income <20K	0.10	0.29	0.0	0.0	0.0	1.0	1.0
Income 20-50K	0.28	0.45	0.0	0.0	0.0	1.0	1.0
Income 50-75K	0.28	0.45	0.0	0.0	0.0	1.0	1.0
Income 75-100K	0.17	0.38	0.0	0.0	0.0	1.0	1.0
Income 100-150K	0.11	0.32	0.0	0.0	0.0	1.0	1.0
Income >150K	0.06	0.24	0.0	0.0	0.0	1.0	1.0
Education: Bachelor	0.49	0.50	0.0	0.0	0.0	1.0	1.0
Education: Master	0.17	0.38	0.0	0.0	0.0	1.0	1.0
Education: Some College	0.16	0.37	0.0	0.0	0.0	1.0	1.0
Marital status: Married	0.57	0.50	0.0	0.0	1.0	1.0	1.0
Marital status: Divorced	0.05	0.21	0.0	0.0	0.0	0.0	1.0
Age	37.05	11.59	18.0	23.0	34.0	60.0	85.0

Table A1: **Self-reported book preferences and demographics of participants in the main experiment.**

Panel A. Geographical location of participants in the main experiment



Panel B. Geographical distribution of the U.S. population (2021 Census)

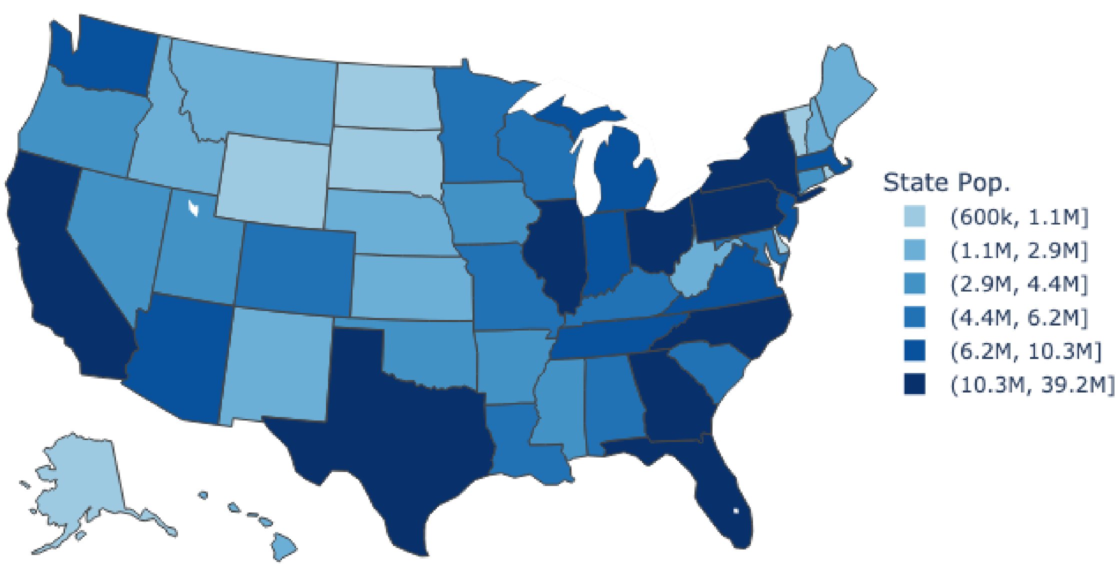


Figure A2: **Sample representativeness.** The graph compares the geographical distribution of participants across U.S. states in our main experiment (top panel) with the distribution of the general population as reported in the 2021 U.S. Census (bottom panel).

	Est.	S.E.	P-value
Lost Girls Plain Ad	0.028	0.025	0.250
Lost Girls Genre Ad	0.021	0.025	0.399
Lost Girls Price Ad	0.004	0.025	0.880
Stateline Plain Ad	0.021	0.025	0.395
Stateline Genre Ad	0.005	0.025	0.825
Stateline Price Ad	0.043	0.025	0.079
Constant	0.804	0.022	0.000

Table A2: **Attrition analysis.** This table analyzes whether the treatment groups experienced differential attrition from the point of treatment assignment to the point of returning to complete the Qualtrics survey. The last row of the table reports the average attrition rate for the control condition, it's standard error and the associated p-value. For the remaining rows in the table, Column 1 reports the difference between that group's average attrition rate and that of the control group. Columns 2 and 3 report the associated standard errors and p-values.

D Experiment Validation

D.1 Internal Validation: Does Our Experiment Elicit Realistic Behavior?

Our goal in this experiment was to create a store that would induce participants to make realistic book choices. To understand whether we achieved this goal, we present several validation analyses. First, we use experimental data to verify that consumers engage in meaningful search in our store and make choices consistent with their self-reported preferences. As shown in Figure A3 and in the left panel of Figure A5, consumers engage in active search. Consumers spend, on average, 3.7 minutes when shopping in our bookstore. The average consumer opens 4.0 pages in the product list, which includes pages in the default-sorted list as well as any pages opened after applying filters, sorting books by price, or using search queries. There is substantial heterogeneity in how much consumers search: around 35% of consumers only view the first page of the assortment, and at the other extreme, 15% of consumers open at least 10 pages. The average consumer also visits 3.3 product pages, including revisits, and searches 1.9 unique books.

We find that the observed book choices align with participants' self-reported genre preferences. Figure A4 plots the probability of purchasing a book of a specific genre as a function of which

	No Ads	Book 1 Genre	Book 1 Plain	Book 1 Price	Book 2 Genre	Book 2 Plain	Book 2 Price	F-test p-val
Fantasy rank	2.858	2.862	2.876	2.899	2.940	2.885	2.927	0.745
Mystery rank	2.550	2.510	2.593	2.551	2.575	2.597	2.523	0.596
Romance rank	3.374	3.285	3.374	3.280	3.262	3.300	3.304	0.628
Scifi rank	2.993	3.055	2.928	2.999	2.970	3.019	3.010	0.423
Memoirs rank	3.225	3.289	3.229	3.270	3.253	3.200	3.236	0.817
BooksPerMonth	1.537	1.668	1.711	1.729	1.685	1.678	1.670	0.206
EbooksPerMonth	1.871	1.968	1.992	2.050	1.984	1.973	1.982	0.441
Female	0.584	0.561	0.544	0.548	0.555	0.574	0.579	0.477
Black	0.108	0.102	0.093	0.110	0.109	0.099	0.101	0.848
Hispanic	0.084	0.049	0.056	0.061	0.055	0.054	0.049	0.299
Asian	0.071	0.030	0.033	0.030	0.029	0.038	0.037	0.020
Income <20K	0.111	0.099	0.097	0.090	0.113	0.103	0.118	0.315
Income 20-50K	0.274	0.309	0.289	0.259	0.279	0.266	0.279	0.157
Income 50-75K	0.226	0.260	0.301	0.299	0.297	0.288	0.265	0.029
Income 75-100K	0.176	0.172	0.164	0.183	0.160	0.179	0.178	0.759
Income 100-150K	0.125	0.109	0.099	0.114	0.102	0.104	0.115	0.731
Income >150K	0.088	0.051	0.050	0.055	0.049	0.060	0.045	0.099
Age	37.007	37.524	37.882	36.872	37.236	38.024	37.454	0.230
Bachelor	0.463	0.488	0.509	0.479	0.483	0.495	0.469	0.507
Master	0.216	0.174	0.196	0.197	0.185	0.184	0.168	0.313
Some College	0.166	0.154	0.147	0.138	0.161	0.146	0.164	0.563
Married	0.595	0.572	0.609	0.584	0.603	0.583	0.562	0.250
Divorced	0.051	0.043	0.039	0.046	0.042	0.048	0.046	0.942
N Participants	296	1,188	1,194	1,155	1,176	1,257	1,213	

Table A3: **Randomization checks.** Columns 1-7 report the means of pre-treatment covariates among participants assigned to each of the seven experimental conditions in the main experiment. Column 8 reports the p-value of the F-test, in which the null hypothesis is that the population means of a given covariate are identical across experimental conditions. The last row of the table reports the number of participants assigned to each experimental condition.

genre the consumer reported liking most. All five figures show that a consumer is about twice as likely to purchase a book in their most preferred genre than a book of any other genre offered in the store. For example, a consumer purchases a fantasy book with a 26% probability if their most preferred genre is fantasy and with only a 5-13% probability if they prefer some other genre. Table A4 additionally describes the distribution of purchases across different subcategories of books by genre and price. Reassuringly, we do not observe that consumers focus their purchases on a few books on the front page, which is what we would see if their only goal was to quickly finish the study and get their cash bonus. In fact, all 100 books in the assortment are purchased at least once (column 3), and the purchases are not overly concentrated on one popular book, even within each subcategory (columns 5-9). Within most genre subcategories, consumers are more likely to buy inexpensive books that cost under $1.00; however, some consumers do purchase more expensive books. Our incentive-compatible experiment design has therefore made consumers price sensitive, but not overly so because we do not see them always choosing the most inexpensive books to maximize the cash bonus. Based on these results, we conclude that our experiment design has elicited meaningful search behavior and has induced consumers to make realistic choices that align with their book preferences.

D.2 External Validation: Search Behavior of Actual Amazon Consumers

We now compare our data to an external dataset that tracks the search behavior of real consumers in the category of books on Amazon. We analyze the Comscore Web-Behavior Panel 2019-2020, which includes approximately 2 million U.S. households. Households install software on their computers that tracks their online browsing activity on all websites and logs their online transactions. These data enable us to identify all instances in which a household visited a product page on Amazon–not necessarily for a book.

We then classify all product page visits into product categories using a dataset of Amazon products obtained from a third-party service, Keepa, that repeatedly tracks product pages on Amazon. Using these additional data, we restrict the dataset to product pages of books, and we identify all

Price/Genre	Category Purch. Share	Num Books Offered	Books Without Orders	Orders Total	Orders Top 1 Book	Orders Top 2 Book	Orders Top 3 Book	Orders Top 4 Book	Orders Top 5 Book
0.00-0.99 Bio,Memoir	0.049	4	0	564	279	183	75	27	0
1.00-1.99 Bio,Memoir	0.133	11	0	1,529	641	330	147	96	80
2.00-3.00 Bio,Memoir	0.023	5	0	264	103	75	38	35	13
0.00-0.99 Fantasy	0.020	2	0	226	118	108	0	0	0
1.00-1.99 Fantasy	0.006	1	0	67	67	0	0	0	0
2.00-3.00 Fantasy	0.092	17	0	1,059	310	245	112	70	56
0.00-0.99 Myst,Thriller	0.256	9	0	2,941	1,453	586	214	202	165
1.00-1.99 Myst,Thriller	0.014	4	0	157	73	35	25	24	0
2.00-3.00 Myst,Thriller	0.023	7	0	266	94	63	32	27	26
0.00-0.99 Romance	0.089	11	0	1,021	499	120	101	89	60
1.00-1.99 Romance	0.011	1	0	131	131	0	0	0	0
2.00-3.00 Romance	0.111	8	0	1,281	720	384	64	32	25
0.00-0.99 Sci-Fi	0.107	9	0	1,227	389	195	134	120	115
1.00-1.99 Sci-Fi	0.017	2	0	192	122	70	0	0	0
2.00-3.00 Sci-Fi	0.050	9	0	573	329	133	26	23	19
Total All Categories	1.000	100	0	11,498	5,328	2,527	968	745	559

Table A4: **Book purchases made by the experiment participants.** The table reports statistics on the number of books, number of orders, and market shares of each genre-price categorization.

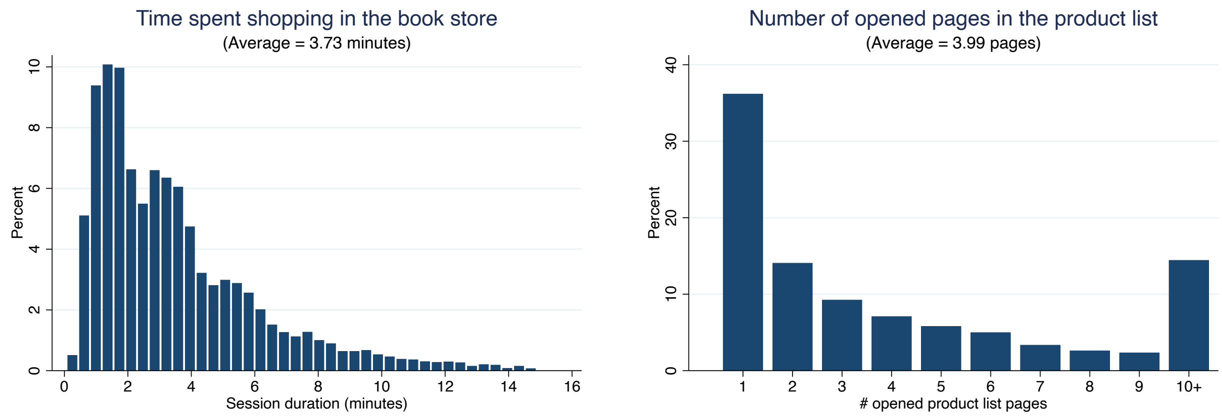


Figure A3: **Consumer search behavior observed in the experiment.** The left graph shows the distribution of store visit durations (in minutes) across participants. The right graph shows the distribution of the number of product list pages opened in the store during the visit. The number of visited product list pages includes pages in the default sorted list as well as any pages opened after applying filters, sorting books by price, or using search queries. The distribution in the right graph is truncated at 10, so the last bar includes all participants who visited 10 pages or more.

books that fall into the same five categories that are represented in our store: biography/memoir, fantasy, mystery/thriller, romance, and science fiction. Given that we populated the store using books sold on Amazon, the definitions of book genres in our dataset are fully consistent with the genre categories we observe in the Keepa dataset.[35]

Having defined relevant product page visits, we restrict the sample to households that "searched" (i.e., visited the product page of) at least one book from the five genres in question. We treat each day as a separate "search session," so a household that searched for books on three different days will appear in the data as three separate observations. These selection steps leave us with a sample of 171,429 households, with each household searching in 4.6 sessions on average. We combine the search data with users' online transactions, also obtained from Comscore, and we compare the extent to which the distribution of searches and purchases across genres matches our observations in our experiment.

Figure A5 visualizes the number of unique books searched by each consumer in a typical search session, comparing the distribution in Comscore data (left panel) and in our experimental

[35]We do not distinguish between searches of electronic and paper books because Keepa's dataset does not have this information.

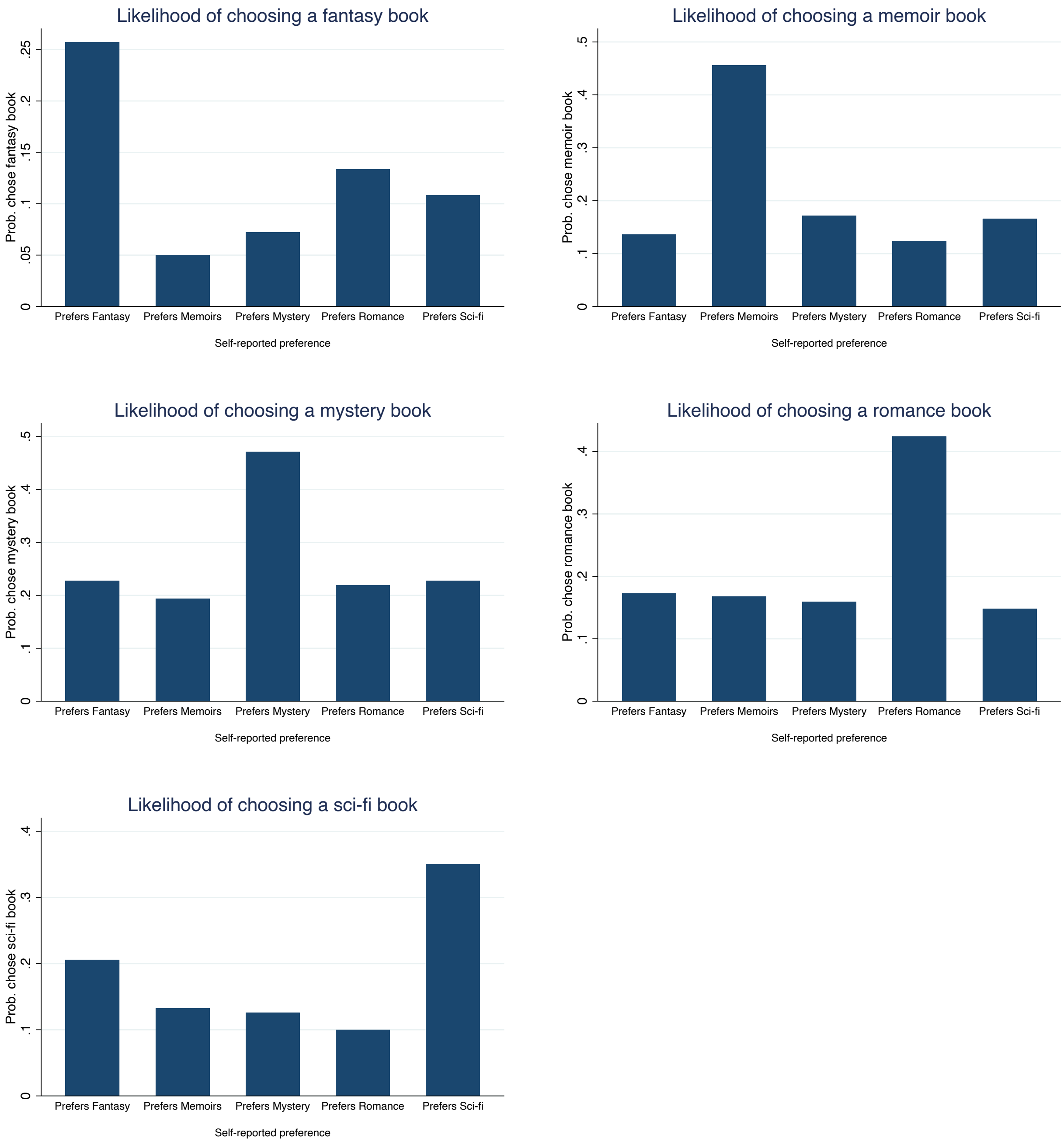


Figure A4: **Book genre choices of consumers with different self-reported genre preferences.**

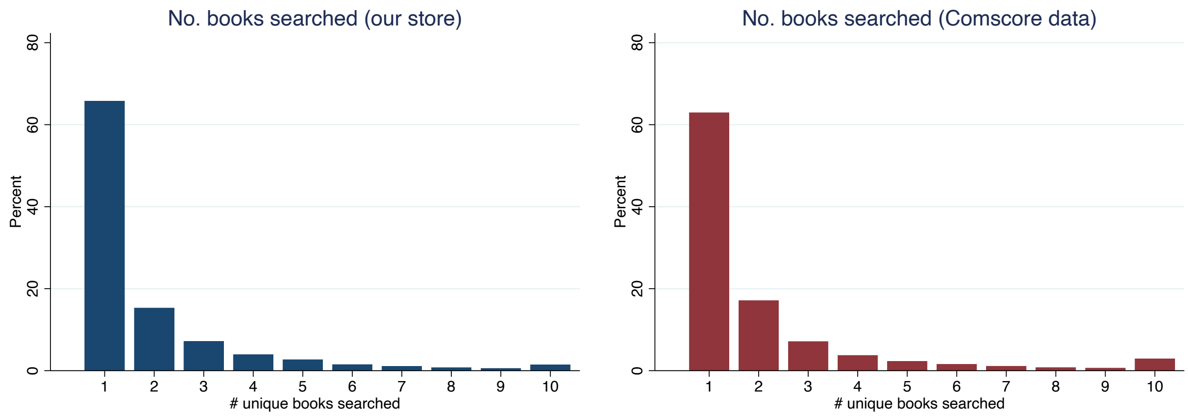


Figure A5: **Number of unique books searched during the session.** The left panel shows the distribution of the number of searches in our bookstore, whereas the right panel reproduces this distribution using Comscore data that describe the behavior of actual Amazon consumers.

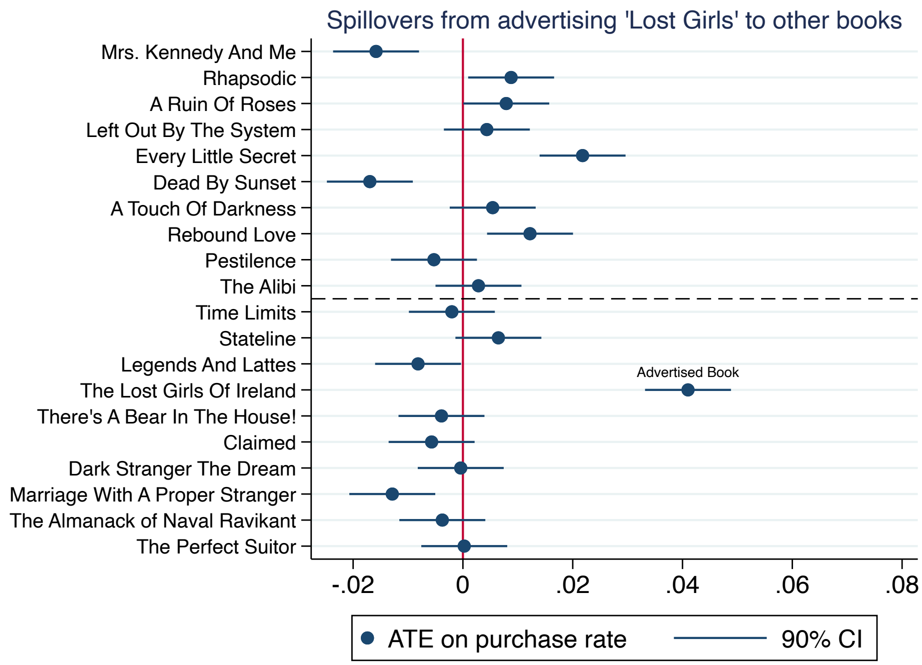
dataset (right panel). We find that the two distributions look almost identical. Consumers search little in both datasets: around 62% of consumers search only one book, 18% search two books, and less than 3% search ten books or more. The average number of searches is 2.19 in Comscore data, which is similar to the 1.93 in our sample. It is reassuring that consumers in our experiment search as much as Amazon customers, which supports the idea that our store elicits realistic search behavior.

E Spatial Spillovers

As we explain in Section 5.5, we find strong evidence of "location" spillovers in our experiment. In Figure A6, we visualize the effects of advertising *Lost Girls* and *Stateline* on the purchase rates of the 20 books located on the first two pages of the store. Each graph orders books by their ranking in the default list. As expected, advertising substantially increases the purchase rate of the advertised books, consistent with strong advertising effects in Table A5. Interestingly, we also find that advertising lifts demand for books located close to the advertising banner. At the 10% significance level, advertisements for *Lost Girls* increase demand for four books: *Rhapsodic* (rank 2), *A Ruin of Roses* (rank 3), *Every Little Secret* (rank 5), and *Rebound Love* (rank 8). At the same time, these ads reduce demand for *Mrs. Kennedy and Me* (rank 1) and *Dead by Sunset* (rank 6). We find virtually identical effects for the advertisements for *Stateline*.

While these effects are not directly predicted by spatial search models, they are consistent with the following attention hypothesis. A salient advertising banner draws consumers' attention to itself while generating attention spillovers to other nearby books. Such attention spillovers would explain why advertising increases demand for books located directly under the advertising banner. An interesting puzzle in Figure A6 is why advertising reduces the purchase rate of the books in the first and sixth positions. We speculate that, given the store layout, consumers naturally examine the assortment from top to bottom and from left to right, which generates position effects. The advertising banner may then disrupt the normal flow of search and weaken the position effects. Such an effect may explain why the two books in the leftmost column of the first page lose popularity. The excess demand is then re-distributed toward appealing books that are located closer to the banner. This phenomenon would explain why advertising increases demand for the book *Every Little Secret*, which has the highest purchase rate (12.6%) among books in our assortment. A promising direction for future research might be to further test this "attention spillover" hypothesis by randomizing the location of the ad banner.[36]

[36]One could randomize both the location of the ad banner in the store and the rankings of books, thus varying the location of the advertising banner relative to the organic listings of non-advertised books. Eye-tracking software may also help reveal whether the advertising banner changes how consumers visually examine books on store pages.



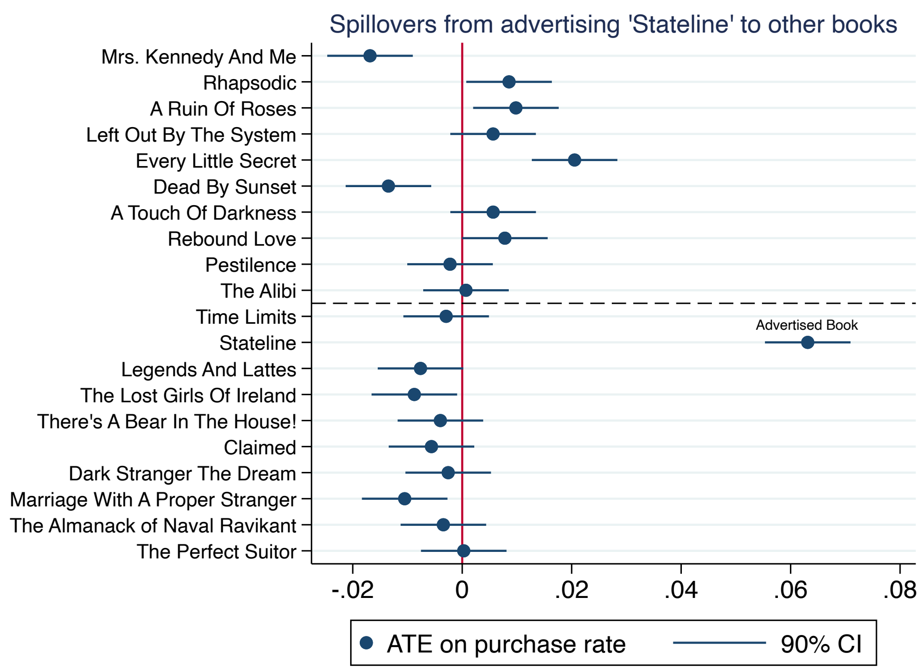


Figure A6: **Advertising effect spillovers on purchase rates of other books.** The graph shows the estimated ATE of any ad for *Lost Girls* (top panel) and *Stateline* (bottom panel) on the purchase rates of other books offered in the store. The graph reflects the average effects of ads regardless of their content. The books are ordered by their position in the product list, with *Mrs. Kennedy and Me* located in position 1, *Rhapsodic* in position 2, and so on. The dashed line separates the front page of the store (positions 1-10) from the second product list page (positions 11-20).

F Additional Figures and Tables

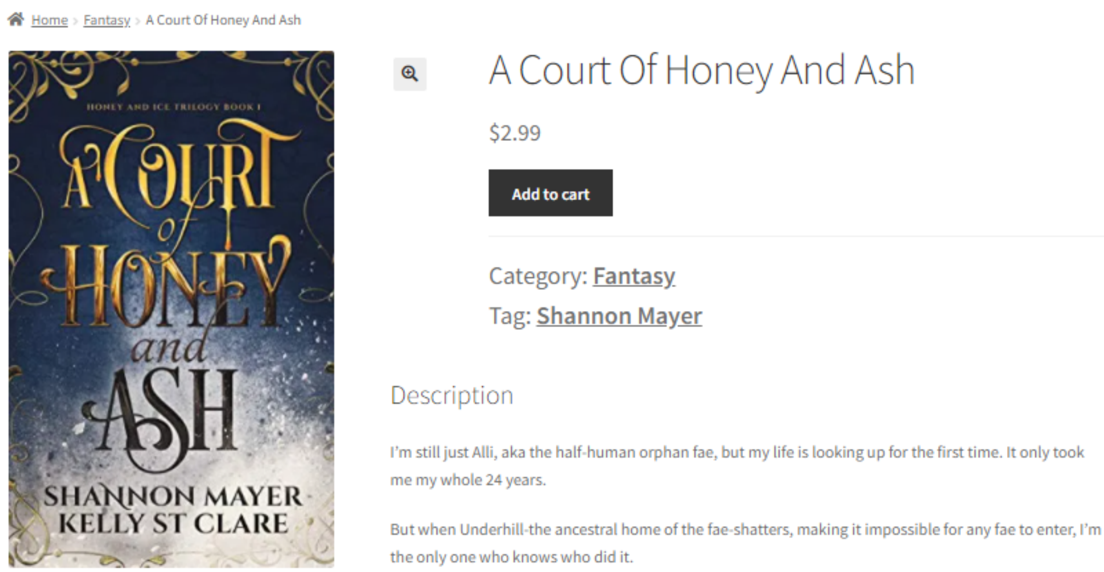


Figure A7: **An example of a product page.**

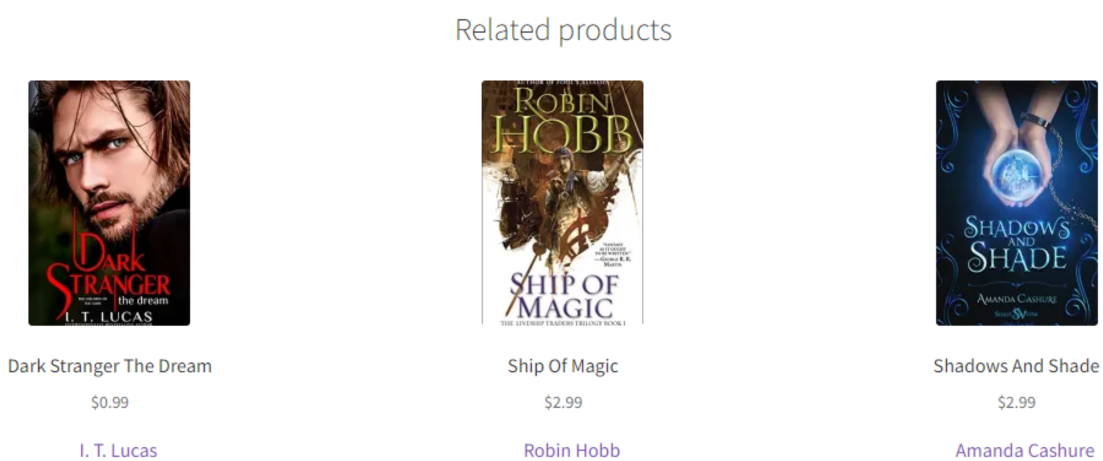


Figure A8: **An example of recommendations on a product page.**

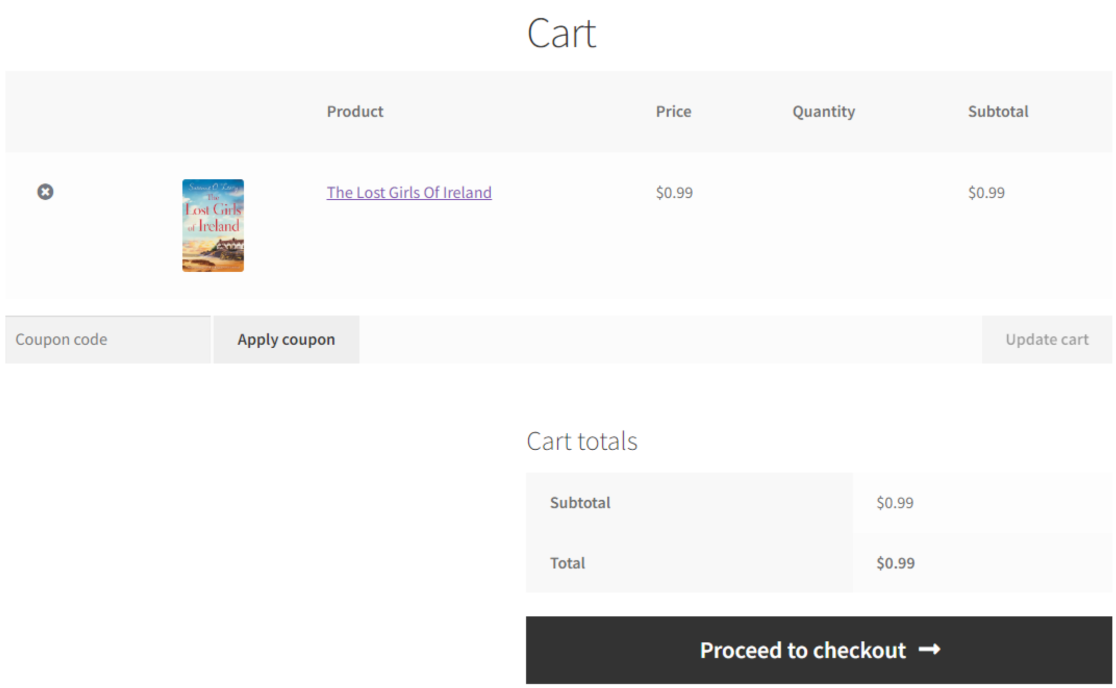


Figure A9: **Shopping cart in our bookstore.**

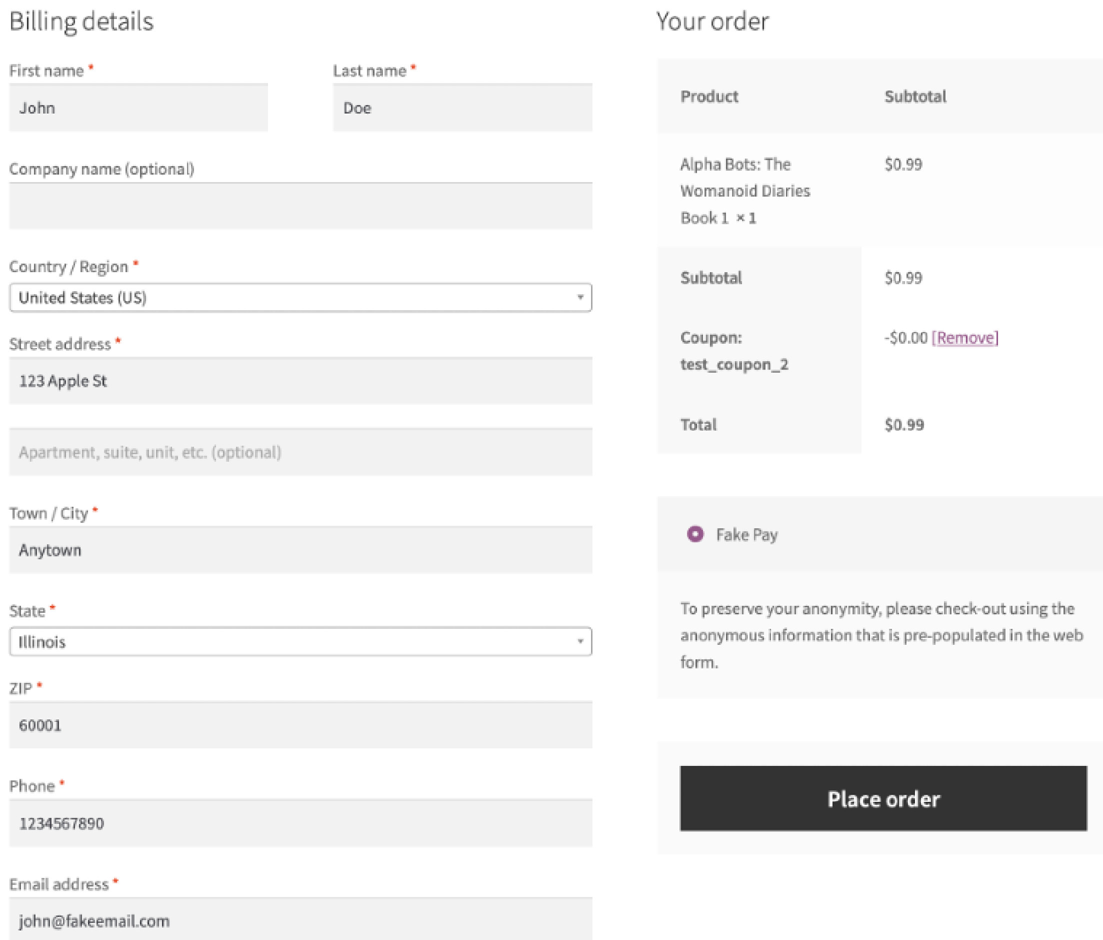


Figure A10: **Checkout page in our bookstore.**

Figure A11: **Display advertisements of books on barnesandnoble.com.**

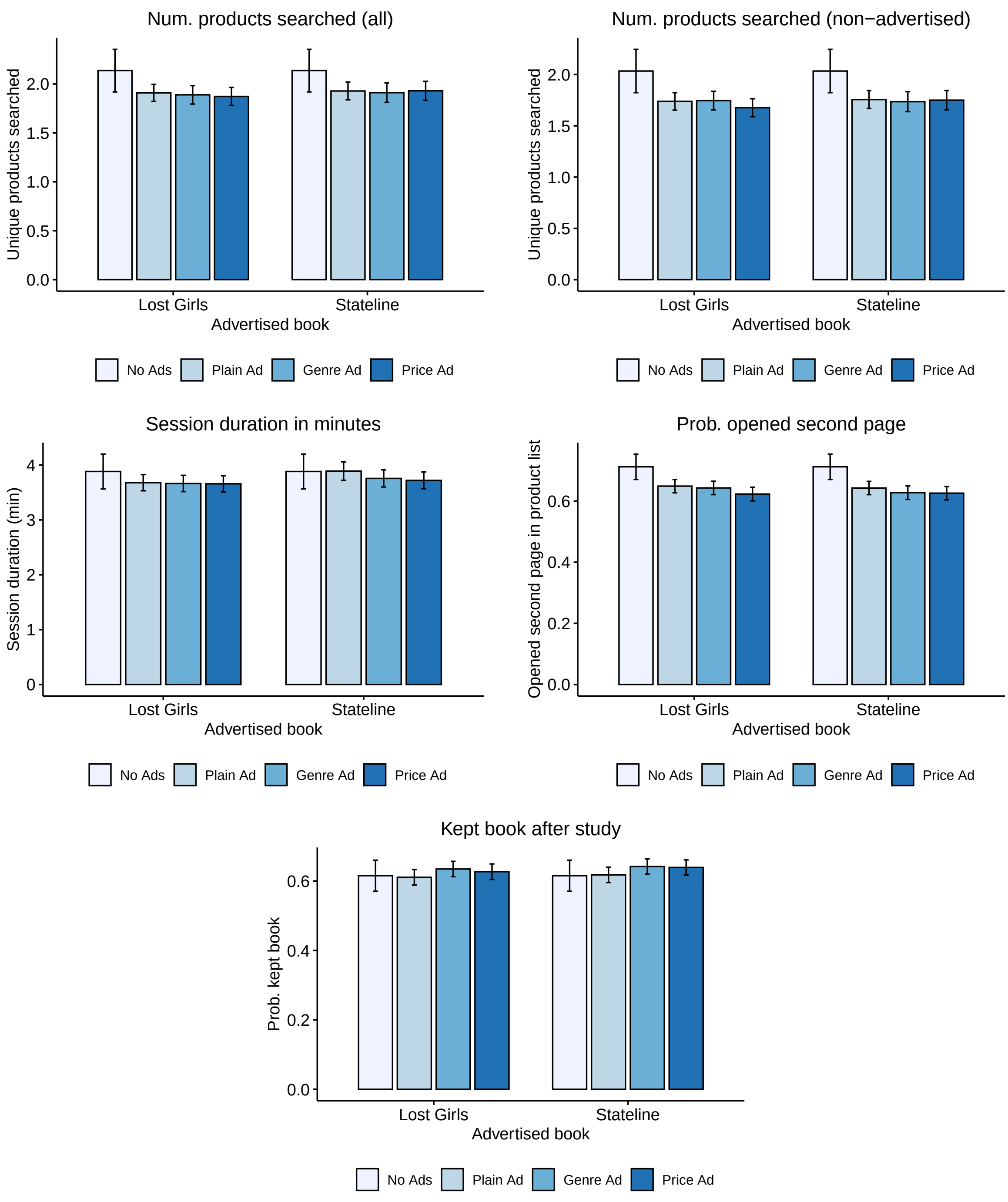


Figure A12: **The effects of ad content on consumer search intensity.**

	No Ad	Plain Ad	$\hat{\beta}$	S.E.	p-value
Panel A. Plain advertising for Lost Girls					
Prob. viewed organic listing	0.719	0.660	-0.058	0.024	0.014
Prob. searched	0.052	0.123	0.071	0.013	0.000
(1) Via ad banner	0.000	0.070	0.070	0.006	0.000
(2) Organic	0.050	0.052	0.002	0.011	0.871
(3) Recommended	0.002	0.001	-0.002	0.002	0.467
Prob. added to cart	0.028	0.067	0.039	0.010	0.000
Prob. purchased book	0.028	0.065	0.037	0.010	0.000
Prob. kept the book	0.024	0.044	0.020	0.009	0.019
Prob. redeemed book	0.008	0.013	0.005	0.009	0.606
Panel B. Plain advertising for Stateline					
Prob. viewed organic listing	0.727	0.658	-0.070	0.023	0.003
Prob. searched	0.050	0.122	0.072	0.013	0.000
(1) Via ad banner	0.000	0.059	0.059	0.005	0.000
(2) Organic	0.050	0.056	0.006	0.011	0.573
(3) Recommended	0.000	0.004	0.004	0.001	0.008
Prob. added to cart	0.019	0.078	0.058	0.009	0.000
Prob. purchased book	0.017	0.074	0.057	0.009	0.000
Prob. kept the book	0.011	0.049	0.038	0.007	0.000
Prob. redeemed book	0.000	0.013	0.013	0.005	0.008

Table A5: **The effects of plain advertising on the advertised book.** Panel A shows the estimated effects of the plain ad for *Lost Girls* on this book's search and purchase outcomes, whereas Panel B shows the same estimates for *Stateline*. We consider a book "searched" if the consumer visited the book's product page at least once. In rows 3-6 of each panel, we distinguish between clicks on the ad banner, clicks on the organic listing of the book, and clicks on the book in a recommendations carousel. Channel-specific search probabilities need not add up to the total search probability because consumers can visit the same product page multiple times via different channels. The variable "kept the book" reflects whether the consumer purchased the advertised book and decided to keep it after the study. The variable "redeemed the book" reflects whether the consumer selected the book, received it in the lottery, and redeemed it after the study.

	Plain Ad	Price Ad	$\hat{\beta}$	S.E.	p-value
Panel A. Advertising for Lost Girls					
Prob. search Lost Girls:					
Consumers who ranked romance 1st	0.108	0.159	0.051	0.026	0.051
Consumers who ranked romance 2nd-5th	0.127	0.142	0.015	0.013	0.223
Prob. buy Lost Girls:					
Consumers who ranked romance 1st	0.079	0.116	0.036	0.023	0.113
Consumers who ranked romance 2nd-5th	0.062	0.076	0.015	0.009	0.113
Panel B. Advertising for Stateline					
Prob. search Stateline:					
Consumers who ranked mystery 1st	0.157	0.158	0.001	0.022	0.972
Consumers who ranked mystery 2nd-5th	0.108	0.127	0.019	0.012	0.134
Prob. buy Stateline:					
Consumers who ranked mystery 1st	0.100	0.085	-0.014	0.018	0.419
Consumers who ranked mystery 2nd-5th	0.065	0.086	0.021	0.010	0.041
Panel C. Pooling Both Books					
Prob. search advertised book:					
Consumers who ranked ad genre 1st	0.139	0.158	0.020	0.017	0.244
Consumers who ranked ad genre 2nd-5th	0.118	0.135	0.017	0.009	0.059
Prob. buy advertised book:					
Consumers who ranked ad genre 1st	0.092	0.097	0.005	0.014	0.717
Consumers who ranked ad genre 2nd-5th	0.063	0.081	0.018	0.007	0.010

Table A6: **The effects of price ads on search and purchase probabilities.** The table reports estimated effects of price ads for *Lost Girls* (top panel), for *Stateline* (middle panel), and for both books with data pooled across all conditions (bottom panel). Each panel reports the means of the outcome variable in the two experimental conditions (columns 1-2), the estimated effect of revealing price information relative to plain ads (column 3), and robust standard errors and p-values (columns 4-5). We split participants into two groups based on their stated genre preferences: participants who ranked the advertised genre first form one group, and all other participants comprise the other.

	No Ad	Plain Ad	$\hat{\beta}$	S.E.	p-value
Panel A. Plain advertising for Lost Girls					
Prob. viewed organic listing	0.719	0.660	-0.035	0.021	0.103
Prob. searched	0.052	0.123	0.071	0.014	0.000
(1) Via ad banner	0.000	0.070	0.070	0.007	0.000
(2) Organic	0.050	0.052	0.002	0.012	0.877
(3) Recommended	0.002	0.001	-0.002	0.002	0.524
Prob. added to cart	0.028	0.067	0.038	0.010	0.000
Prob. purchased book	0.028	0.065	0.036	0.010	0.000
Prob. kept the book	0.024	0.044	0.021	0.009	0.021
Prob. redeemed book	0.008	0.013	0.006	0.011	0.573
Panel B. Plain advertising for Stateline					
Prob. viewed organic listing	0.727	0.658	-0.037	0.021	0.078
Prob. searched	0.050	0.122	0.069	0.013	0.000
(1) Via ad banner	0.000	0.059	0.058	0.006	0.000
(2) Organic	0.050	0.056	0.006	0.012	0.624
(3) Recommended	0.000	0.004	0.002	0.001	0.054
Prob. added to cart	0.019	0.078	0.055	0.009	0.000
Prob. purchased book	0.017	0.074	0.055	0.009	0.000
Prob. kept the book	0.011	0.049	0.035	0.007	0.000
Prob. redeemed book	0.000	0.013	0.012	0.006	0.056

Table A7: **The effects of plain advertising on the advertised book (conditional on observables).** This table replicates the results from Table A5, additionally controlling for pre-treatment covariates. See the notes of Table A5 for additional details.

	Search Est.	Search S.E.	Search P-value	Purch. Est.	Purch. S.E.	Purch. P-value
ATE Regression Estimates (Lost Girls):						
β Plain ad	0.070	0.014	0.000	0.033	0.010	0.001
β Genre ad	0.049	0.013	0.000	0.027	0.010	0.007
β Price ad	0.093	0.014	0.000	0.052	0.011	0.000
Implied ATE differences:						
β Genre $-$ β Plain	-0.021	0.011	0.046	-0.007	0.008	0.420
β Price $-$ β Plain	0.023	0.011	0.049	0.019	0.009	0.034
β Price $-$ β Genre	0.044	0.011	0.000	0.026	0.009	0.004
ATE Regression Estimates (Stateline):						
β Plain ad	0.069	0.013	0.000	0.054	0.009	0.000
β Genre ad	0.083	0.013	0.000	0.062	0.009	0.000
β Price ad	0.082	0.013	0.000	0.062	0.009	0.000
Implied ATE differences:						
β Genre $-$ β Plain	0.013	0.011	0.240	0.007	0.009	0.409
β Price $-$ β Plain	0.012	0.011	0.279	0.008	0.009	0.388
β Price $-$ β Genre	-0.001	0.011	0.927	0.000	0.009	0.972

Table A8: **Estimated advertising effects on searches and purchases (conditional on observables).** This table replicates the results from Table 1 in the main text, additionally controlling for pre-treatment covariates. See the notes of Table 1 for additional details.

	Plain Ad	Genre Ad	$\hat{\beta}$	S.E.	p-value
Panel A. Advertising for Lost Girls					
Prob. search Lost Girls:					
Consumers who ranked romance 1st	0.108	0.140	0.027	0.027	0.316
Consumers who ranked romance 2nd-5th	0.127	0.092	-0.032	0.012	0.007
Prob. buy Lost Girls:					
Consumers who ranked romance 1st	0.079	0.102	0.014	0.024	0.563
Consumers who ranked romance 2nd-5th	0.062	0.049	-0.012	0.009	0.151
Panel B. Advertising for Stateline					
Prob. search Stateline:					
Consumers who ranked mystery 1st	0.157	0.220	0.063	0.026	0.015
Consumers who ranked mystery 2nd-5th	0.108	0.097	-0.008	0.012	0.501
Prob. buy Stateline:					
Consumers who ranked mystery 1st	0.100	0.125	0.026	0.021	0.211
Consumers who ranked mystery 2nd-5th	0.065	0.063	-0.001	0.010	0.939
Panel C. Pooling Both Books					
Prob. search advertised book:					
Consumers who ranked ad genre 1st	0.139	0.189	0.051	0.018	0.006
Consumers who ranked ad genre 2nd-5th	0.118	0.094	-0.020	0.008	0.017
Prob. buy advertised book:					
Consumers who ranked ad genre 1st	0.092	0.116	0.024	0.015	0.113
Consumers who ranked ad genre 2nd-5th	0.063	0.056	-0.006	0.007	0.318

Table A9: **Match value effect of genre advertising (conditional on observables).** This table replicates the results from Table 2 in the main text, additionally controlling for pre-treatment covariates. See the notes of Table 2 for additional details.

Pooling Both Books	Plain Ad	Attribute Ad	$\hat{\beta}$	S.E.	*p*-value
Panel A. Spillovers from price ads:					
Sorted by price low-to-high	0.233	0.230	-0.002	0.010	0.810
Sorted by price high-to-low	0.033	0.028	-0.003	0.004	0.423
Searched other cheap books	0.514	0.507	-0.010	0.011	0.386
Bought another cheap book	0.419	0.424	-0.000	0.011	0.989
Self-reported price importance	3.029	3.042	0.008	0.031	0.808
Panel B. Spillovers from genre ads:					
Filtered to advertised genre	0.017	0.017	-0.000	0.003	0.912
Filtered to any genre	0.060	0.070	0.009	0.006	0.121
Searched other books of advertised genre	0.282	0.287	-0.004	0.011	0.674
Bought another book of advertised genre	0.199	0.208	0.004	0.009	0.695
Self-reported genre importance	4.011	3.998	-0.016	0.025	0.525

Table A10: **Advertising spillovers to similar non-advertised books (conditional on observables).** This table replicates the results from Table 3 in the main text, additionally controlling for pre-treatment covariates. See the notes of Table 3 for additional details.